Essays on Water Quality Management for the Chesapeake Bay Watershed

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ABSTRACT

Water quality management for agricultural production is a complicated and interesting problem. Hydrological and economic factors must be considered when designing strategies to reduce nutrient runoff from agricultural activities. This dissertation is composed of three chapters that investigate cost-effective ways to mitigate water pollution from agricultural nonpoint pollution sources and explore farmers' incentives when participating in water quality trading programs.

Chapter 1 investigates landscape targeting of best management practices (BMPs) based on topographic index (TI) to determine how targeting would affect costs of meeting nitrogen (N) loading goals for Mahantango watershed, Pennsylvania. We use the results from two climate models and the mean of the ensemble of seven climate models to estimate expected climate changes and the Soil and Water Assessment Tool-Variable Source Area (SWAT-VSA) model to predict crop yields and N export. Costs of targeting and uniform placement of BMPs across the entire study area (4.23 km^2) are compared under historical and future climate scenarios. We find that with a goal of reducing N loadings by 25%, spatial targeting methods could reduce costs by an average of 30% compared with uniform BMP placement under three historical climate scenarios. Cost savings from targeting are 38% under three future climate scenarios. Chapter 2 scales up the study area to the Susquehanna watershed (71,000 km^2). We examine the effects of targeting the required reductions in N runoff within counties, across counties, and both within and across counties for the Susquehanna watershed. We set the required N reduction to 35%. Using the uniform strategy to meet the required N reduction as the baseline, results show that costs of achieving a regional 35% N

reduction goal can be reduced by 13%, 31% and 36% with cross-county targeting, within-county targeting and within and across county targeting, respectively.

Results from Chapters 1 and 2 suggest that cost effectiveness of government subsidy programs for water quality improvement in agriculture can be increased by targeting them to areas with lower N abatement costs. In addition, targeting benefits are likely to be even larger under climate change.

Chapter 3 investigates the landowner's nutrient credit trading behavior when facing the price uncertainty given the credits are allowed to be banked for future use. A two-step decision model is used in this study. For the first step, we determine the landowner's application level of a BMP on working land in the initial time period. The nutrient credits awarded to the landowner depend on the nutrient reduction level at the edge of field generated by the BMP application. For the second step, we use an intertemporal model to examine the landowner's credit trading behavior with stochastic price fluctuations over time and with transaction costs. The theoretical framework is applied with a numerical simulation incorporated with a hydro-economic model and dynamic programming. Nutrient Management (NM) is selected as the BMP on working land to generate N credits. We find that gains to the landowner from credit banking increase with higher price volatility and with higher price drift, but that gains are larger with price volatility. However, for a landowner holding a small amount of nutrient credits, the gains from credit banking are small due to transaction costs.

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GENERAL AUDIENCE ABSTRACT

Two considerations are critical for efforts to mitigate nutrient runoff from nonpoint sources: cost effectiveness of strategies to reduce nutrient runoff and landowners' incentives to participate in these programs. This dissertation is composed of three manuscripts, aiming to evaluate the cost effectiveness of government subsidy programs for water quality management in agriculture and investigate the landowner's incentives to participate in water quality trading programs for the Chesapeake Bay watershed. Chapter 1 investigates gains from targeting Best Management Practices (BMPs) under current and future climate conditions based on the soil characteristics relative to uniform BMP application for a small experimental watershed (4.23km^2). Chapter 2 scales up the study area to a 71,000 km^2 watershed and treats each county within the watershed as a representative farm to explore economic gains from targeting within county and across county based on counties' physical conditions and agricultural patterns. Both Chapters show that cost-effectiveness of government subsidy programs can be improved by spatial targeting BMPs to areas with lower abatement costs. Gains from targeting increase under climate change. In Chapter 3 we shows how a landowner's revenues from nutrient credit selling will be affected if the credits are allowed to be banked for future use when she faces price uncertainty. We find that gains to the landowner from credit banking increase more with higher price volatility than with higher price drift. Gains from banking are largely reduced by transaction costs associated with trading.

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1.1 Introduction

The Chesapeake Bay watershed, covering more than 166,000 square kilometers across six states (New York, Maryland, Virginia, West Virginia, Pennsylvania and Delaware) and the District of Columbia, contains the largest estuary in the United States (Cooper, 1995). Agricultural production is one of the major human activities within the watershed, and intensive agricultural activities represent the largest single source of nutrients, contributing 44% and 58% of the total nitrogen (N) and phosphorus (P) discharged to the Chesapeake Bay, respectively (Chesapeake Bay Program, 2015). To mitigate the nutrient pollution and improve water quality, US EPA has set up a Total Maximum Daily Load (TMDL) program to improve water quality, which employs Best Management Practices (BMPs) and wastewater treatment plant upgrades to achieve nutrient reduction goals including a 25% N loading reduction by 2025 (US EPA, 2010a; US EPA, 2010b).

Best Management Practices are an effective way to reduce soil erosion, prevent N loss and improve water quality (Rao et al., 2009). However, because of the variability in soil, land use pattern, topography, climate, and other site-specific characteristics, the effectiveness of a BMP in terms of N loading reduction varies across different sites and spatial scales within a watershed (Rao et al., 2009). Spatial targeting of BMPs according to runoff potential can improve water quality (Wagena and Easton, 2018), and reduce the costs to farmers and taxpayers of achieving water quality goals. Numerous studies have found that targeting BMPs to sites with higher pollution potential can improve cost effectiveness of pollution reduction efforts (Khanna et al., 2003; Yang and Weersink, 2004; Yang et al., 2005 and Giri et al. 2012). Studies have shown that targeting BMPs or a land retirement payment scheme by flow paths, sub-catchment, soil erodibility, or other land and soil characteristics instead of applying BMPs randomly or uniformly can reduce costs of meeting a given water quality goal (Khanna et al., 2003; Yang and Weersink, 2004; Yang et al.,2005). Although targeting methods are more effective than uniform or arbitrary BMP placement, different targeting criteria may be needed for sediment, phosphorus, or nitrogen. For instance, Giri et al. (2012) demonstrated that targeting BMPs by Load per Subbasin Area Index (LPSAI) results in the most significant reductions for sediment and phosphorus, whereas targeting BMPs by Concentration Impact Index (CII) is most effective for nitrogen reduction.

Climate change impacts agricultural output and pollution potential (Walthall et al., 2013), but the effects on pollution loadings are unclear. For instance, greater and more variable rainfall increases N loading, but this may be balanced by increased denitrification under warmer temperatures (Jeppesen et al., 2011; Kosten et al., 2012; Wagena et al., 2018). As a result, the cost and effectiveness of BMPs and the gains from targeting BMPs may vary as the climate changes. While there is extensive literature on targeting BMP placement to achieve water quality goals under current climate conditions, few studies have evaluated the effects of climate change on water quality targeting strategies or on the economic consequences of BMP targeting. We hypothesize that increased variability of N loadings under climate change will alter the optimal choice of BMPs and BMP placement and increase the gains from targeting BMPs compared to gains realized by targeting under current climate conditions.

The purpose of this study is to evaluate the effects of climate change on potential farm-level cost savings from spatial targeting of water quality BMPs. Bosch et al. (2018) evaluated effects of climate change on costs of achieving water quality goals in this watershed using a farm economic model in combination with SWAT-VSA forced with climate model predictions. We extend that model to examine the possibility of targeting BMPs based on a Topographic Index (TI), a measure of soil runoff risk that combines upslope contributing area and local slope gradient (Easton et al., 2008; Collick et al., 2015).

1.2 Materials and methods

1.2.1 Study area

We carried out the study in WE-38, a 7.3 km^2 sub-watershed of Mahantango Watershed, located in Northumberland County, Pennsylvania (Figure 1.1). WE-38 has been extensively studied as a USDA Agricultural Research Service experimental watershed beginning in 1966 (Bryant et al., 2011). The total area of the WE-38 sub-watershed is 730 ha with 54.9% cropland, 3.2% pasture, 39.6% woodland, and 2.3% developed (Bryant et al., 2011). The crop (400 ha) and pasture area (23 ha) are the focus of this study.

1.2.2 Soil and Water Assessment Tool-Variable Source Area (SWAT-VSA)

We use SWAT-VSA (Soil and Water Assessment Tool-Variable Source Area) model from Easton et al. (2008), a derivative of the SWAT model, to predict the N loss from agricultural landscapes and evaluate the effectiveness of BMPs subject to climate change. The SWAT model is a watershed-scale, physical model incorporating weather, soil, land cover and land management data to simulate surface and subsurface hydrology and various chemical and sediment fluxes (Collick et al., 2015). Spatial data for SWAT include soils, land use and elevation. SWAT-VSA replaces the commonly used STATSGO or SSURGO soil layer with a spatial combination of the FAO-UNESCO Digital Soil Map of the World (FAO, 2007) and topographically-derived soil wetness TI class (Easton et al. 2008). After dividing a catchment into Hydrologic Response Units (HRUs), we use SWAT-VSA to estimate crop yields and N loadings and evaluate the environmental effectiveness of BMPs at the HRU scale. In this study, we use the TI to classify the soil into 10 equal area wetness classes from the least runoff prone (1) to the most runoff prone (10) (Easton et al., 2008). The total cropland area in each TI class is 40 ha and the total pasture area is 2.3 ha.

The WE-38 SWAT-VSA model was calibrated and evaluated using SWAT-CUP (SWAT Calibration and Uncertainty Procedure) (Arnold et al., 2012) using the SUFI2 (Sequential Uncertainty Fitting) optimization algorithms with the objective function set to the Nash Sutcliffe Efficiency coefficient (NSE). The SWAT-VSA model performance was evaluated based on three metrics, percent bias (PBIAS), coefficient of determination (R^2), and the NSE, against the historical measured data from 1989 to 1999 for model calibration and 1999 to 2007 for model evaluation. For further details see Wagena et al. (2018).

1.2.3 Climate prediction model

Results from seven climate models were obtained from the North American Climate Change Assessment Program (NARCCAP) model dataset (Mearns *et al.*, 2009). The models use dynamical downscaling—nesting a regional climate model (RCM) within a global climate model (GCM)—and provide data at high temporal (3-hourly) and spatial (50-km) resolutions, better capturing local processes

(Rummukainen, 2010). Greenhouse gas concentrations in the NARCCAP future simulations are obtained from the medium-high SRES A2 emissions scenario (Nakicenovic *et al.*, 2000). For a more detailed description of the climate models refer to Wagena et al. (2018). Then for each climate scenario, SWAT-VSA generates estimated crop yields and N loadings from each TI class for a given land use. We evaluated seven climate change models from NARCCAP for the estimation of future crop yields and N loading levels by TI class. We ranked the estimated N loadings per hectare for six crops: alfalfa, corn, wheat, soybean, rye, and pasture and averaged the ranks of results from seven models over the soil TI classes. From the seven climate models, we selected two: 1) WRFG-CGCM3 (Weather Research & Forecasting Model, Third Generation Coupled Global Climate Model) which ranked highest in terms of absolute predicted yield differences between future and historical climates; and 2) CRCM-CCSM (Canadian Regional Climate Model, Community Climate System Model), which ranked lowest in terms of predicted yield differences. In addition, we used the mean yield and loading predictions generated by the ensemble of seven models, which we refer to as the Ensemble Mean model. Each model was used to represent climate variables under historical (1975 to 1998) and future (2045 to 2068) conditions.

1.2.4 Economic model

The farm model maximizes the total gross margin from crop and livestock production, subject to land, machinery, crop rotation, crop nutrition, livestock facilities, livestock feeding, and N loading constraints. Crop and pasture production are limited to 400 hectares of cropland and 23 hectares of pasture. Crop rotations include continuous corn, continuous grass pasture, one-year corn one-year soybean, two-year corn three-year alfalfa, one-year corn two-year alfalfa, corn followed by double-cropped wheat and soybeans, and corn or soybean followed by rye cover. In addition, the farm can produce corn as silage or grain.

Because of limits on machinery and labor time within the available days suitable for fieldwork, the maximum areas for growing corn, full season soybeans, double-cropped soybeans, and wheat are 231, 186, 191, and 240 hectares, respectively (USDA, 2015). In addition, we set a constraint that the farm can buy or raise alfalfa for feed, but cannot sell alfalfa given the primary focus of the farm on dairy and poultry production.

Crop costs/ha (including labor and machinery, but excluding land and fertilizer) for corn grain, corn silage, full season soybean, double crop wheat/soybean, alfalfa hay establishment, and alfalfa hay are $912, $1,384, $467, $971, $679, and $759 (2015$), respectively. The model calculates fertilizer costs separately depending on nutrient source. Crop nutrients mainly come from legume N carryover, commercial fertilizers, or manure (Penn State, 2015). Crop prices/Mg (2015$) for corn grain, corn silage, soybean, wheat and alfalfa hay are $235, $57, $471, $247, and $187, respectively.

Livestock facility limits constrain the dairy to 80 cows and the number of broilers to 1 broiler house with production of 242,000 birds/year (Rhodes, et al., 2011). Total gross revenue from dairy cows is $4,463 per cow per year. Costs per cow including purchased feed, veterinary supplies, breeding fees, calf-raising costs, milk hauling, building, machinery, utility, and labor costs are $2,614/cow unit/year. The model calculates costs of farm raised feed and manure spreading separately. The model can meet feed requirements by purchase and/or on-farm production. Crop feed requirements per lactating cow per year include 1.41 Mg corn grain, 13.74 Mg corn silage, 1.5 Mg alfalfa and 0.25 hectares of pasture. Total annual gross revenue of the broiler house is $70,674 with variable costs of $16,820. The poultry integrator supplies feed for broilers.

Some characteristics of the farm such as number of cows and broilers are selected to be representative of the surrounding county and differ from actual watershed conditions.

Manure production includes 21,087 liters liquid manure per lactating cow, 8.6 Mg solid manure produced by heifers and dry cows per lactating cow equivalent, and 376 Mg litter per broiler house annually. Per unit sale prices for these three manures are $−0.002/L, $0, and $15.7/Mg, respectively.

Net returns are optimized subject to constraints using linear programming (McCarl and Spreen, 1997). The model is coded using the General Algebraic Modeling System (GAMS Development Corporation, 2018).

1.2.5 BMPs

Six BMPs are assessed (Table 1.1): conservation tillage, stream buffers, cover crops, crop nutrient management, off-stream watering without fencing for livestock, and land retirement. These are the most cost-effective BMPs for the Chesapeake Bay watershed (Chesapeake Bay Foundation, 2015).

Conservation tillage in this study means continuous no tillage. Compared with conventional tillage, the implementation of no tillage could bring 10.5% N reduction ha and costs -$111 ha annually (Devereux and Rigelman, 2014). Cover crops are considered as an effective way to enhance the soil structure and prevent N from running-off (Ritter et al., 1998). Non-harvested rye and commodity wheat are included as cover crops in this study.

Nutrient management (NM) prevents pollutant loading from excessive nutrient applications. There are three tiers of NM containing various combinations of practices, effectiveness, and costs (Table 1.1). Tier 1 NM consists of the estimation of crop yields based on farm records or the rated soil production capacity of the field, and taking account of N contributions from the soil, manure applications, and legume carryover, when estimating fertilizer N application rates. Tier 2 NM contains all Tier 1 activities and soil lab analysis as well as contemporary guidelines from state programs necessary for proper nutrient source, rate, timing, and placement to improve nutrient use efficiency. Tier 3 NM includes all Tier 2 practices. In addition, Tier 3 NM requires an Illinois Soil N Test (ISNT), Corn Stalk Nitrate Test (CSNT), Pre-side dress Nitrate Test (PSNT), or Fall Soil Nitrate Test (FSNT) resulting in changes in net N applications for the field (Devereux and Rigelman, 2014; Nutrient Management Expert Panel, 2015).

A stream buffer involves placing grass strips as filters along streams to delay or reduce loadings from upslope contributing areas to surface water bodies. Effectiveness of stream buffers has been widely proven (Azzaino et al., 2002; Yang et al., 2014). In this study, grass buffers consist of a 10-meter wide planting along streams, reducing N loading up to 32% (Devereux and Rigelman, 2014). Annual costs for establishing and maintaining the buffer area are $471/ha. The model calculates separately the opportunity cost of the buffer, which is the foregone income when the farmer removes land from cropping for the buffer. The stream buffer reduces loadings of N from the buffer area itself and four times as much upslope area. Therefore, the area treated by the stream buffer is five times the actual buffer area (Devereux and Rigelman, 2014; Van Houtven et al., 2012). The allowable area for buffers from TI class 1 to 10 are 0.40 ha, 0.43 ha, 0.43 ha, 0.33 ha, 0.38 ha, 0.57 ha, 0.22 ha, 0.38 ha, 0.36 ha and 3.70 ha, respectively. The total area eligible for buffers is 7.20 ha and the area treated by the buffer is 36.0 ha.

Livestock watering in streams are a source of N pollution. Off-stream watering without fencing limits the tendency of livestock to enter the stream for drinking and therefore reduces the stream bank erosion from livestock and pollution from livestock defecating in the stream (Dillaha et al., 2009). The maximum area that can be treated by off-stream watering is equal to the total pasture area, 23 ha.

Land retirement is an important nonpoint source pollution control method under the Conservation Reserve Program (CRP). Land retirement reduces N loading by taking agricultural lands out of production for at least 10 years. Soils targeted are those with poor soil conditions and in close proximity to streams. Such soils, when cultivated, generate pollutants at higher than average rates. Landowners who enroll receive an annual rental payment for retired land, $295.39/ha based on the rental payment in Pennsylvania (USDA, 2016). The maximum land enrolled in the land retirement program cannot exceed 25% of total agricultural land in production per farm (Stubbs, 2014).

1.2.6 Conceptual framework

The first step to estimating effects of climate change on gains from targeting is to estimate the farmer's costs of meeting a required reduction in nutrient loadings under historical ($j = 0$) and future ($j = 1$) climate scenarios and for uniform and targeted placement of BMPs. The cost is equal to the reduction in farm net revenue under the constraint compared to a baseline with no constraint on nutrient loadings. The second step is to estimate the reductions in the cost of meeting the nutrient loading constraint under targeting compared to uniform placement of BMPs. The reductions in cost represent the economic gains from targeting. The third step is to compare the reductions in costs with targeting under future climate with cost reductions from targeting under current climate conditions.

Costs of meeting the nutrient loading constraint

Costs of meeting the constraint are estimated assuming that the farmer maximizes net revenue from agricultural production for a farm subject to constraints including the requirement that the farmer reduce N loading by 25 percent. Let *m* denote an index of TI class, where $m = 1,2,\ldots,M$. Because the study area is a small watershed, we assume only one farm across the whole watershed. Let x_{cm} denote the level of crop *c* on TI class *m* $(c = 1,2,\ldots,C)$, and let x_i denote livestock level $(i = 1,2,\ldots,I)$.

Let π_{cm} denote the per unit net revenue from crop *c* on TI class *m* and π_i denote the per unit net revenue from livestock i. The farmer's objective is to maximize *E(x)* the total expected farm revenue from the watershed, which is the sum of the expected per unit crop (π_{cm}) or livestock (π_i) net revenue times the number of crop and livestock units.

(1) $Max\ E(x) = \sum_{c=1}^{C}\sum_{m=1}^{M}\pi_{cm} * x_{cm} + \sum_{i=1}^{I}\pi_i * x_i$

Expected net revenue is maximized subject to

(2) $\sum_{m=1}^{M} a_{km}x_{cm} \leq b_{ck}$

Equation (2) describes conventional resource constraints, including land, rotation, and machinery for crops; a_{km} denotes the amount of constraint k required per unit of the farm and b_{ck} denotes the amount available of constraint *k* for crop c.

In addition, there are requirements to meet crop nutrient needs

(3) $\sum_{m=1}^{M} n_{cmr}x_{cm} \geq w_{cr}$

Equation (3) describes the nutrient (N, phosphorus, and potassium) requirement of crop production, where n_{cmr} denotes the amount of nutrient *r* applied per unit crop c and TI class m and w_{cr} is the total requirement of nutrient r for crop c.

Livestock production is also subject to constraints

(4) $f_{pi}x_i \leq s_{pi}$

Equation (4) is a set of livestock production constraints including livestock facilities. f_{pi} denotes the amount of constraint p required per unit of livestock i and s_{pi} denotes the total amount of available p for livestock i.

Livestock also are subject to feeding requirements (5)

(5) $e_{hi}x_i \geq q_{ji}$

e_{ji} is the requirement of feed type h per unit of livestock i; and q_{ji} is the total feeding requirement of livestock i for the *hth* feed type.

Equation (6) is the N loading constraint for the farm.

(6) $\frac{\sum_{c=1}^{C}\sum_{r=1}^{R}\sum_{m=1}^{M} d_{rm}x_{cm}}{R} \leq (1 - G_e) * \sum_{m=1}^{M} t_m$, r $= 1,2, \dots.,$ R

The left side of the equation represents average loadings from crops where the area of each crop and TI class (x_{cm}) is multiplied by d_{rm} the per unit area loading for the farm in state r. A state corresponds to a climate pattern for a growing season under either the current climate or a future climate scenario. The summation of the product of per ha loading for crop and pasture times the total ha crop and pasture for the farm is the total loadings in each state. Loadings are summed over all states and divided by the number of states (R) to obtain an average. The right side of equation 6 represents the constraint on loadings. The average N loading level over all states must be less than or equal to the required N loading level, where G_e is the reduction set for the environmental goal (expressed as a decimal fraction) and t_m represents the baseline (unconstrained) loading from soil TI class m. We investigate targeting strategies when reductions of nitrogen loadings are set at 25%.

Under the baseline, the constraint on nutrient loadings is not binding and expected returns are maximized. When the nutrient reduction constraint is imposed, farm net returns are reduced below those of the baseline and the reduction is the cost of the nutrient loading constraint. Expected returns with the constraint are $E_{uj}(x)$ or $E_{tj}(x)$ when BMPs are uniformly placed or targeted, respectively.

Reduced costs with targeting

The costs of the nutrient loading constraint depend on how the constraint is met, i.e., whether BMPs are uniformly applied (C_{uj}) or targeted (C_{tj}) as described below.

(7) $C_{uj} = E_{ncj}(x) – E_{uj}(x)$,

Costs of the nutrient loading constraint with uniform placement equal expected returns with no constraint minus expected returns with uniform placement (7).

(8) $C_{tj} = E_{ncj}(x) – E_{tj}(x)$.

Costs of the nutrient loading constraint with targeted placement equal expected returns with no constraint minus expected returns with targeting (8).

The reduced costs from targeting (gains from targeting) are equal to the reduction in costs of meeting the N loading constraint with targeting relative to costs with uniform allocation of BMPs (9):

(9) $\triangle C_j = C_{uj} - C_{tj}$, $\mathrm{j} = 0, 1$ where 0 refers to the historical climate scenario and 1 is the future climate scenario.

Effects of climate change on costs

The effects of future climate on gains from targeting (Gt) equal the difference in the gains from targeting under the future climate scenario minus the gains under the historical climate scenario (10).

(10) $Gt = \triangle C_1 - \triangle C_0$

1.2.7 Robustness checking for uncertainty

The model of nutrient loading reductions and associated costs is subject to uncertainty. To deal with the uncertainties, a robustness check of the model focuses on two aspects, the cost predictions for water quality improvements with spatial targeting and gains from targeting compared with the uniform strategies under the historical and future climate scenarios. To test the robustness of cost predictions from the targeting model with 25% N reduction constraint, three prediction uncertainties in terms of costs are considered, the N reduction policy, the farm size and market prices and costs. The following parameters are varied for robustness check of the cost prediction: (1) N reduction goal (30%, 35% and 40%), (2) farm size, including increasing cropland area (by 50%, 100%, 150% and 200%) and livestock number (by 50%, 100%, 150% and 200%) and (3) increasing prices and costs of crops and livestock (by 5%, 10%, 15%, 20% and 25%). The Ensemble mean model with historical and future scenarios are selected for the robustness check.

The results of robustness checks presented in Section 3.3 showed that costs increased nonlinearly as the N reduction goal and farm size (livestock) increased. Therefore, we further evaluated the effects of the N reduction goal and farm size on the gains from spatial targeting compared with uniform strategies under historical and future climate scenarios. Moreover, to explore other possible behavior patterns of farm owners, we simulated a random application of BMPs to meet the water quality goal, which means the farmer neglects soil TI class and applies BMPs arbitrarily in the study area.

1.3 Results

1.3.1 Baseline[1]

SWAT-VSA is used to predict N loadings for current and future climate scenarios

[1] Results of this study are based on the assumption of the farm profit maximization. In some cases actual crop and BMP choices observed in the watershed may deviate from those predicted by profit maximization.

in soils with each TI class (Table App.pp.1.1). The results of ANOVA for differences in means of crop N loading levels across TI classes within climate scenarios and across climate scenarios, at a 5% significant level, indicate the following: wheat differences in loadings are statistically insignificant both across TI classes and across climate scenarios. Corn and soybean differences are statistically insignificant across TI classes, but statistically significant across climate scenarios. Alfalfa differences are statistically insignificant across climate scenarios. However, alfalfa differences are statistically significant across TI classes for the historical climate scenario based on the Ensemble Mean model.

Under the historical scenario with the Ensemble Mean, CRCM, and WRFG models, total estimated N loadings from the farm are 15,679 kg, 15,642 kg and 15,384 kg, respectively. Alfalfa and pasture have lower N loadings, while wheat has the highest N loadings for historical and future climate conditions with all three climate models (Figure 1.2). The variation of N loading levels does not simply follow the increase of the soil TI class. For instance, under the historical scenario with the Ensemble Mean predictions, the lowest N loading from corn is 30.25 kg/ha in TI class 3 and the highest level is 33.63 kg/ha in TI class 4; the lowest N loading from soybean is 22.81 kg/ha in TI class 3 and the highest level is 26.48 kg/ha in TI class 9.

Average yields predicted by SWAT-VSA across TI classes are shown in Figure 1.3. For ANOVA results, at a 5% significance level for alfalfa, corn and wheat, the mean differences of yields are statistically significant across historical and future climate scenarios (Table App.pp.1.2). However for a given climate scenario and crop, the mean differences of yields are statistically insignificant across TI classes. Alfalfa yields increase while wheat, corn, and soybean yields decline under climate change.

For the Ensemble Mean, CRCM, and WRFG models, total gross margins (TGM) decline 15%, 16% and 19%, respectively, under the future climate scenario compared to the historical scenario (Figure 1.4, Table App.1.3). TGMs decline because yields of corn, the most profitable crop, decrease under the future climate. Under the Ensemble Mean historical condition, the shadow prices ($/ha) for cropland by TI class from 1 to 10 are 477, 451, 468, 483, 466, 466, 446, 451, 467 and 495, respectively. Taking land from TI class 7 out of production would have the smallest opportunity cost, while TI class 10 would have the highest opportunity cost and should be given lower priority for being placed under CRP.

Total N loadings decline for the future climate scenario compared to historical loadings by 19% (Ensemble Mean), 17% (CRCM) and 23% (WRFG) (Table App.1.3). The decline is due to a shift out of wheat into corn and soybeans which have lower N loadings. Average per ha loadings (kg) by TI class from 1 to 10 equal to 45, 34, 42, 44, 41, 29, 24, 45, 43, and 45, respectively. TI classes 1 and 10 generate the highest per ha loading level from agricultural production among all soil TI classes indicating that they may receive higher priority for CRP allocation. However, TI class 1 also has higher net returns from crop production, which also is taken into consideration when targeting CRP or other BMPs.

Predicted changes in crops from the historical to the future climate scenario are similar for the three climate models (Table App.1.3). Corn grain and full season soybean remain the two major crops. Under the future climate, full season soybean increases by 17, 5, and 9 times under the Ensemble Mean, CRCM and WRFG models, respectively. Double-cropped soybean and wheat decrease to zero in the future climate scenario with all three models. Corn silage and alfalfa production are almost the same between historical and future climate scenarios. CRP is not selected in either historical or future climate scenarios, which implies that net revenues per ha from planting crops are still higher than the CRP rental payment per ha.

1.3.2 Costs of meeting the water quality goal with uniform and targeting strategies

The evaluation of 25% N reduction is based on baseline loading under the historical scenario as predicted by each climate model. Hence, N limits under the historical and future climate scenarios are 11,759 kg (=15,679kg*0.75) for Ensemble mean, 11,732kg (=15,642kg*0.75) for CRCM, and 11,538kg (=15,384kg*0.75) for WRFG.

Uniform strategies mean farmers apply BMPs uniformly across all TI classes to meet this water quality goal. For the same N reduction goal, spatial targeting lets farmers apply BMPs and select crops according to yield and N runoff potential derived from each soil TI class.

Costs of uniform and targeting application of BMPs to meet the water quality goal under both climate scenarios and all three climate models are presented in Figure 1.5. Compared with uniform BMP application, targeting methods reduce costs by 30% and 37% for Ensemble Mean historic and future scenarios, 34% and 43% for CRCM historic and future scenarios, and 27% and 33% for WRFG historic and future scenarios, (Tables A1.4, A1.5, and A1.6). For all climate scenarios, the above results indicate that BMP application with spatial targeting is an important strategy under current as well as future climate scenarios to achieve the water quality goals.

Under the historical climate scenario, farm TGMs increase under BMP targeting relative to the uniform scenario because cover crop wheat and the accompanying double-crop soybean can be produced on higher yielding land rather than being allocated uniformly across TI classes (Tables A1.7 and A1.8). Under the future climate scenario, more cost effective allocation of BMPs and CRP enables the farm to achieve higher returns by producing more acres of corn (Ensemble Mean), slight increases in full season soybean (CRCM and WRFG), and slight reductions in total CRP (CRCM). In addition, under both historical and future scenarios, the allocation of CRP to lower yielding land means that crops can be produced on higher yielding land resulting in higher overall profits from crop production.

Cost savings from spatial targeting are smaller in absolute value under climate change compared to historical conditions while relative savings are larger (Figure 1.5). Smaller cost savings under climate change occur because the N loading restriction is less binding (less N needs to be reduced) under climate change meaning that overall costs are smaller and there are fewer potential savings to be obtained. Further, in 8 of the 12 cases examined for corn, soybean, alfalfa, and wheat, yields per ha declined under climate change (Table App.1.2). Lower yields also reduce the gains from targeting because cost savings from shifting CRP to lower yielding land and reallocating crops to higher yielding land are reduced when overall yields decline.

1.3.3 Robustness checking of uncertainty

When we change the N reduction goal from 25% to 30%, 35% and 40%, and hold all other parameters constant, Figure 1.6 panel (a) shows that the slopes indicating cost increases with increased N reductions are stable for both ensemble history and future. For the variation of farm size parameters (Figure 1.6 panel (b) and (c)), cropland area and livestock number are increased by 50%, 100% and 150% separately; other parameters are held constant. The slope showing cost increases with percent increases in cropland is a bit greater for Ensemble history compared to Ensemble future, but both are still stable when we expand cropland area. Effects of increased livestock are similar with up to 50% increases in livestock, but for further livestock increases costs increase with the historical scenario but not for the future scenario. Predicted costs are more sensitive to changes in livestock number under Ensemble history than under Ensemble future, especially for the 150% increase in livestock numbers. When we increase all prices and costs of agricultural production from 5% to 20%, costs increase in a linear fashion with similar slopes for both historical and future climate scenarios (Figure 1.6 panel (d)).

Figure 1.7 panel (a) indicates that gains from targeting decline under both historical and future climate scenarios when the N reduction goal increases. This result occurs because as N reduction goals increase with a fixed land area, there is less flexibility for targeting in the allocation of CRP and BMPs. However, percentage gains from targeting are still higher under future climate compared to historical climate. For cropland area expansion with 50%, 100% and 150%, the gains from targeting methods compared with uniform application remain at 31% and 37% under Ensemble history and future respectively. When there are 50% and 100% increases in livestock numbers, targeting methods contribute more in the historical scenario than under future climate. With increased livestock numbers, gains from targeting decline under the historical scenario while remaining constant under the future climate scenario (Figure 1.7 panel (b)).

The robustness check about BMPs application methods show that the cost saving from targeting methods compared to uniform application could be viewed as the lower bound for the study area because we only compare targeting with a uniform strategy of placing BMPs over the entire study area. A random allocation of BMPs including CRP could result in higher costs compared to the uniform strategy. Costs of 25% N reduction under random application compared with other two methods (Figure 1.8) are higher than costs under uniform application and targeting methods for both Ensemble history and future.

1.4 Discussion

These results showing the benefits of targeting are in line with findings from previous studies that have addressed the design and performance of targeting BMPs by various soil criteria to control nitrate pollution cost-effectively (Jha et al., 2010; Giri et al., 2012; Willis and Privette, 2017). For instance, Jha et al. (2010) suggested that targeting conversion of row crops to grassland on Highly Erodible Land (HEL), in upper basin and floodplain areas could mitigate N loadings by 47%, 16%, and 8%, respectively, in Squaw Creek watershed, IA. Willis and Privette (2017) examined the cost-effectiveness of BMPs based on targeting the high runoff subbasins for meeting given water quality goals in the Reedy River basin, SC, and found that targeting reduced control cost by at least 26% compared with a uniform control standard for all subbasins.

This study contributes to the targeting literature by targeting BMPs by runoff generating areas (TI). In watersheds dominated by saturation excess runoff, the TI has been found to represent spatial heterogeneity for susceptibility to N runoff more effectively and simply compared to other criteria (Easton et al., 2008). Hence, targeting BMPs by soil TI class could achieve a more cost-effective BMP allocation than other targeting methods that are based on more aggregate soil criteria. This study also contributes by considering the opportunity costs of applying BMPs instead of only calculating BMP implementation and maintenance costs (Wu et al., 2006; Cools et al., 2011 Giri et al., 2014). Opportunity cost is particularly important in the case of CRP, which involves removal of land from production. This study also extends previous analysis to look at how climate change impacts potential cost reductions from spatial targeting, showing that while absolute benefits are smaller, relative benefits of targeting are likely to be larger under future climate scenarios. The effects of climate change on gains from targeting have received little attention in the literature.

The results provide additional encouragement to natural resource managers and policymakers regarding the importance of applying BMPs by targeting methods with finer scale soil criteria. The results suggest that in the future, spatial analytical tools (Geographic Information Systems, remote sensing, and other decision aids) will be important tools for cost-effective implementation of water quality improvements for agriculture.

Uncertainty analysis indicates that model results are robust with respect to increased N reductions, cropland area and prices and costs (Figure 1.6 panel (a), (b) and (d) respectively). However, varying livestock numbers results in large differences in costs between Ensemble history and future climate scenarios (Figure 1.6 panel (c)). The large differences are due to two factors. First, required N reductions are larger under Ensemble historical climate conditions than under Ensemble future climate and the differences become larger when livestock numbers increase. Hence, the marginal N abatement costs under Ensemble history are higher than under the Ensemble future climate scenario. Second, additional reductions of N under the historical scenario are achieved with 90ha of nutrient management as well as increased amounts of manure transport off the farm, both of which involve high costs. The use of nutrient management with manure further reduces the manure revenue under the Ensemble history.

Relative gains from targeting decline with increasing N reduction goals (Figure 1.7 panel (a)) and with increasing livestock numbers under historical conditions (Figure

1.7 panel (b)). Higher N reductions brought on by increased livestock numbers or increased N reduction goals are met by applying nutrient management, the BMP used in managing livestock manure, extensively across all cropland, which reduces the ability of targeting to control costs by allocating the BMP to specific crop areas. In addition, much of the increased cost of N reduction is due to off-farm manure disposal costs, which are not affected by targeting.

Spatial targeting results in higher gains in comparison with random application of BMPs. These gains are larger than were realized with uniform application (Figure 1.8). However, farmers may already be following other strategies such as targeting based on partial information about soil productivity and runoff. Such strategies may incorporate less information compared to the TI class, in which case targeting benefits based on TI class might be smaller than the estimates from our study. Consideration of such strategies is beyond the scope of this paper. However, for water quality management, BMP placement and CRP enrollment, farm and natural resource conservation advisors should encourage farmers to seek out where targeting benefits can be obtained.

1.5 Conclusion

Results of this study suggest that spatial targeting is an important strategy for reducing costs of achieving water quality goals under both historical and future climate scenarios. Targeting methods for BMP placement are always superior to uniform strategies because they increase farm TGMs while achieving the environmental goal under all climates scenarios in which the N loading constraint is binding. Targeting improves returns by converting lands with relatively higher N loading and lower yield potential to CRP thereby reducing the cost of idling land compared to uniform placement.

Researchers, resource program managers, and farmers should monitor climate change impacts on crop production closely to insure that they select optimal combinations of BMPs and crops to meet water quality goals at least cost. Spatial targeting will be an important part of these strategies to adapt climate change and reduce future water quality management cost.

Two areas of further research are suggested. The effects of climate change and changing crop production patterns on relative crop prices should be investigated. Changing relative prices could have important implications for crop production and costs of meeting environmental loading constraints. Second, results for this small watershed should be confirmed for varying farm and watershed conditions.

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Tables

Table 1.1.1 Costs per hectare (2015$) and effectiveness of BMPs

BMPs	N loading reduction (%)	Annualized cost/ ha (2015$)
Conservation tillage	10.50	-111.00
Stream buffers	32.00	471.00
Off-stream watering without fencing	5.00	73.00
Rye cover crop		82.00
Tier 1 NM- both high and low till with manure	9.25	31.32
Tier 1 NM- high till without manure; hay with nutrients	5.00	31.32
Tier 2 NM- high till with manure	4.40	50.30
Tier 2 NM- low till with manure	4.40	182.20
Tier 2 NM- hay with nutrients	2.80	21.43
Tier 3 NM- high till, low till with manure	2.80	2.68
Land retirement	100	-297.50

Source: Bosch et al., (2018)

[a] N loading reductions from cover crops are estimated by SWAT-VSA and vary by soil and TI class. Commodity wheat is also a cover crop. Its costs are included as part of the wheat-double cropped soybean rotation.

Figures

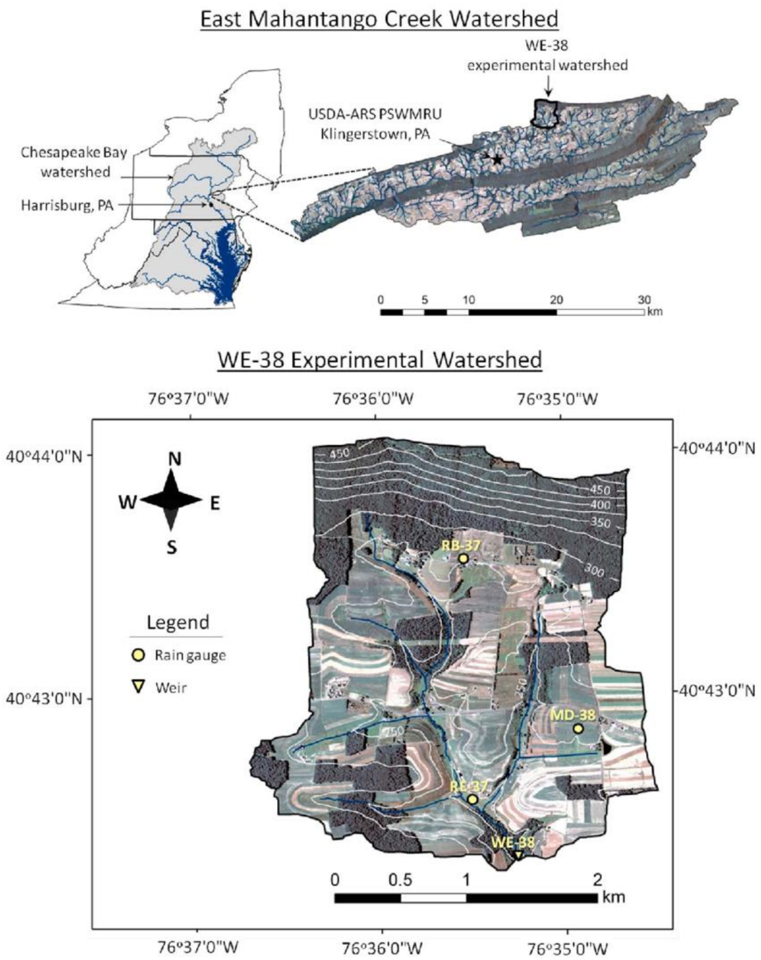

Figure 1.1 WE-38 watershed and location within the Mahantango Creek and Chesapeake Bay watersheds. Source: Modified from Bryant et al, 2011, Figure 1.

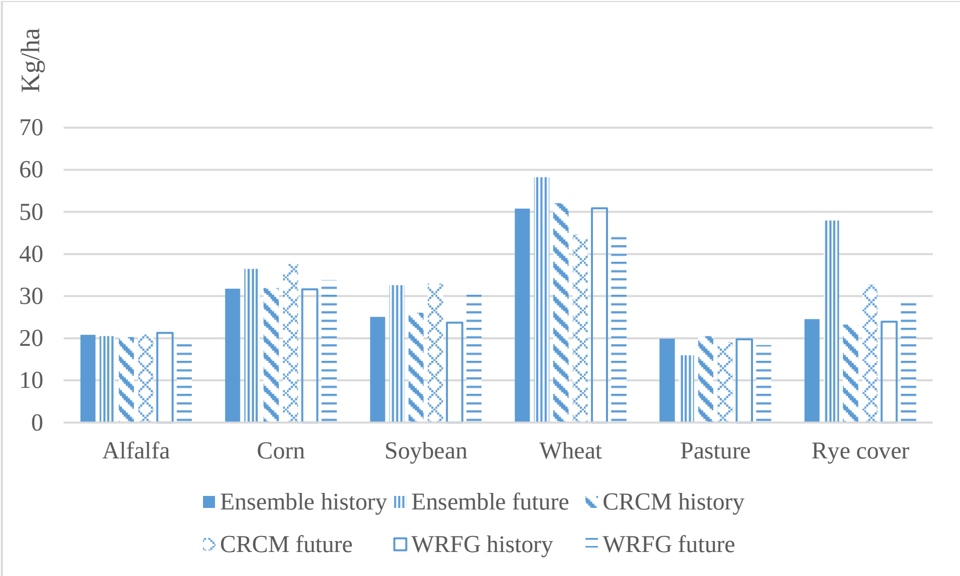

Figure 1.2 N loadings (kg/ha) by climate scenario

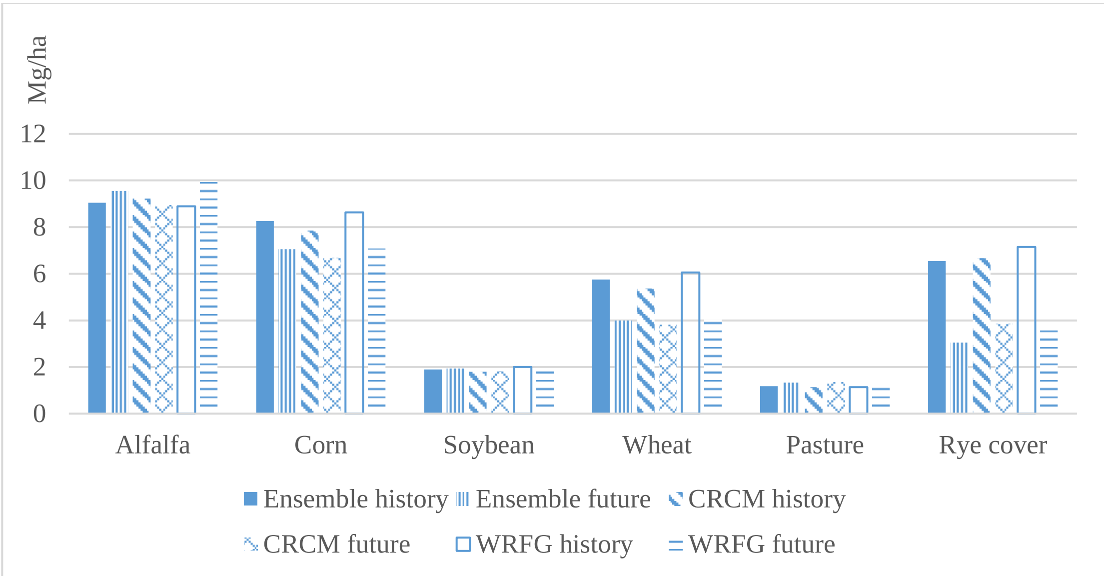

Figure 1.3 Crop yields (mg/ha) by climate scenario

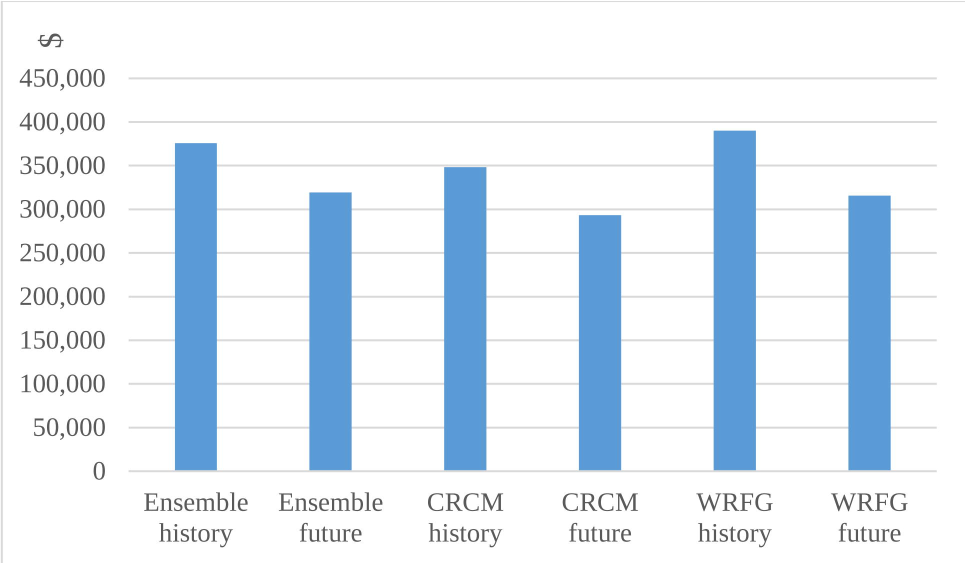

Figure 1.4 Farm total gross margins by climate scenario with no loading constraint

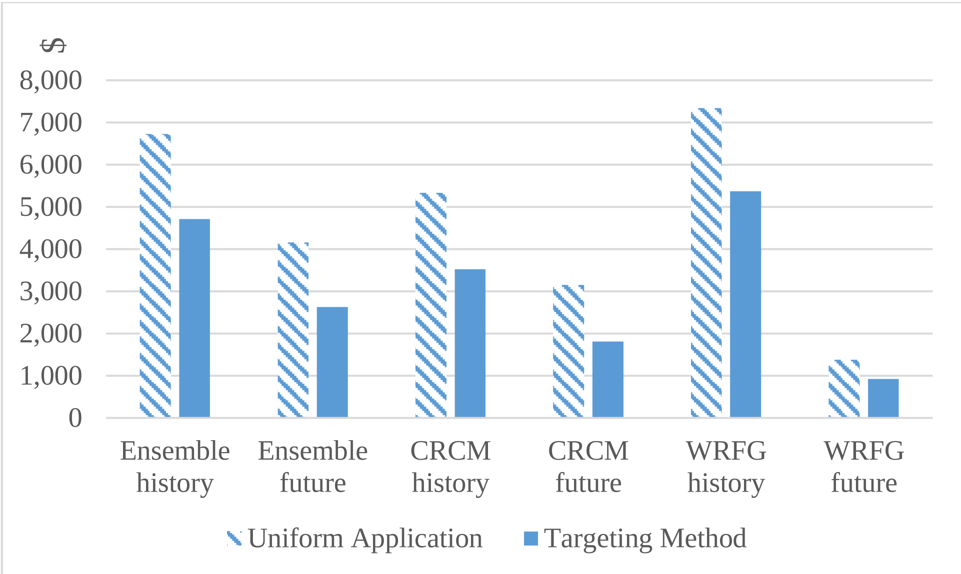

Figure 1.5 Costs (US dollars) of 25% N reduction under two BMP application methods by climate scenarios

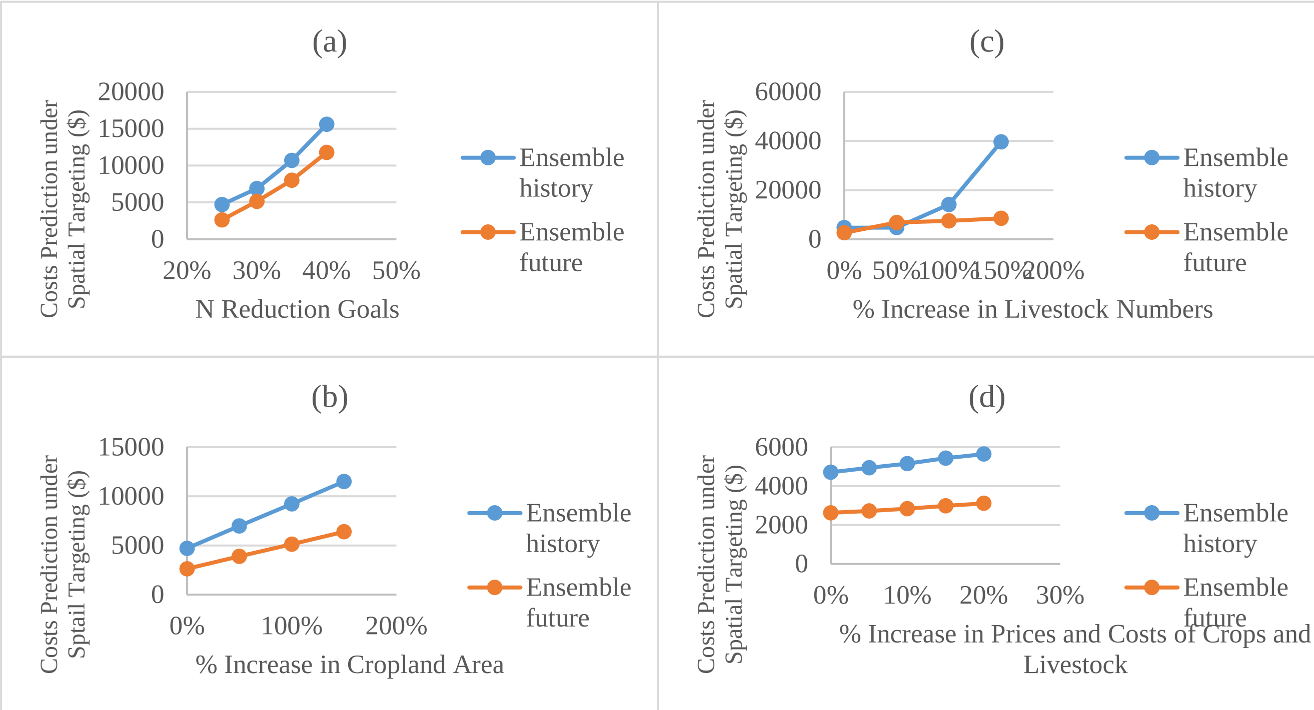

Figure 1.6 Sensitivity analysis of costs prediction under spatial targeting. Panel (a). Changes in N reduction goals. Panel (b). Changes in cropland area. Panel (c). Changes in livestock numbers. Panel (d). Changes in prices and costs of crops and livestock

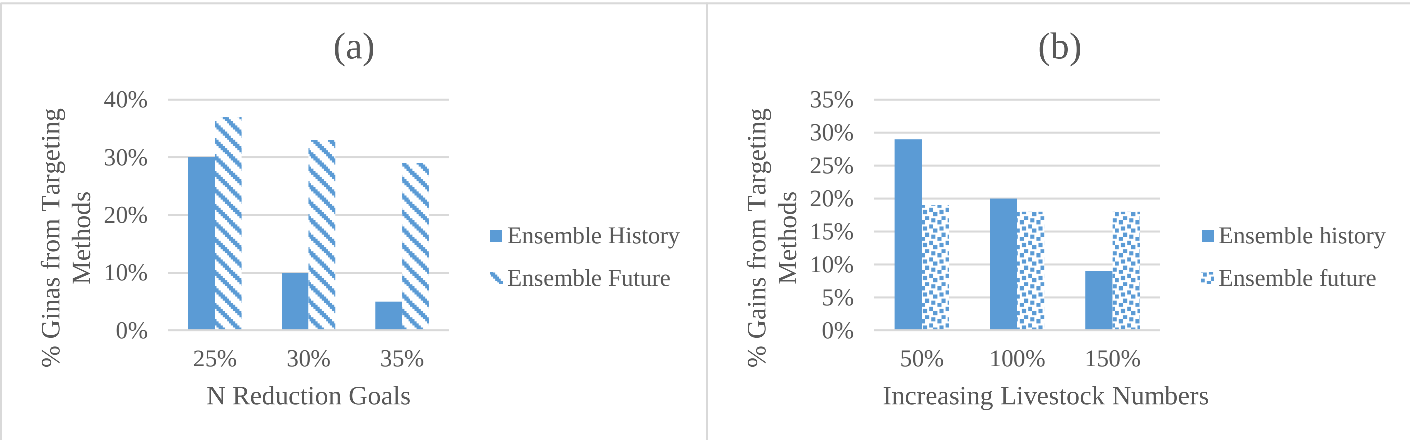

Figure 1.7 Sensitivity of gains from spatial targeting compared with uniform strategies. Panel (a). Changes in N reduction goals. Panel (b). Changes in livestock numbers

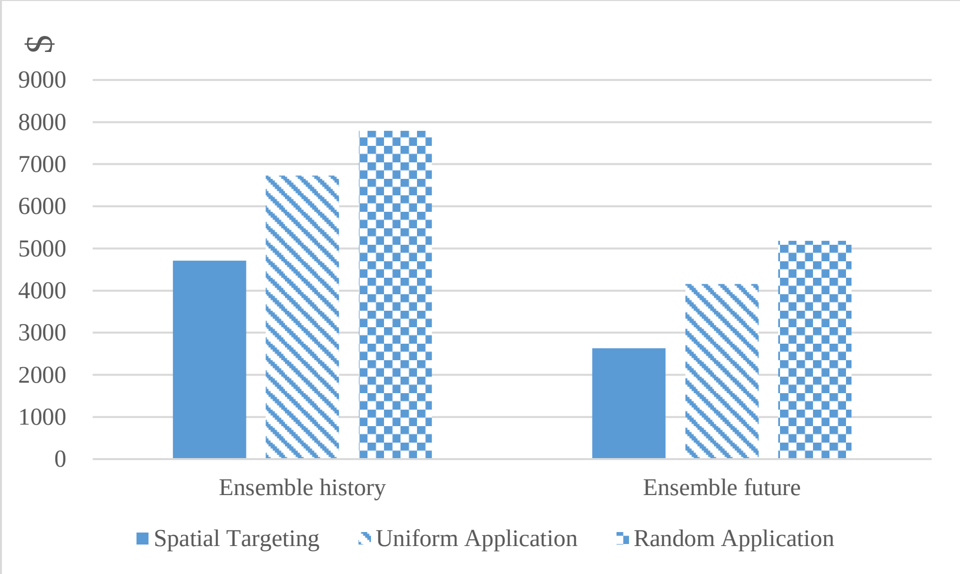

Figure 1.8 Costs comparison between three BMP Application Method

Appendix tables

Table App.1.1 Unconstrained N loading of crops under all climate scenarios

	Baseline N loading of crops (kg/ha)					
Ensemble history	Alfalfa	Corn	Soybean	Wheat	Pasture	Rye cover
Mean	20.8	31.8	25.07	50.77	19.95	24.54
SD	8.39	7.33	8.46	16.06	7.62	11.54
CV	0.4	0.23	0.34	0.32	0.38	0.47
Ensemble future						
Mean	20.52	36.51	32.59	58.27	15.98	47.99
SD	8.18	7.52	6.83	22.51	6.31	9.73
CV	0.40	0.21	0.21	0.39	0.39	0.20
CRCM history						
Mean	20.27	31.95	26.08	52.11	20.52	23.23
SD	9.22	7.44	9.76	22.28	8.13	12.91
CV	0.45	0.23	0.37	0.43	0.40	0.56
CRCM future						
Mean	20.89	37.6	32.99	44.59	19.10	32.75
SD	10.34	13.17	11.32	29.91	9.66	20.58
CV	0.5	0.35	0.34	0.67	0.51	0.63
WRFG history						
Mean	21.29	31.66	23.70	50.90	19.77	23.96
SD	10.17	11.69	9.96	22.78	9.67	14.50
CV	0.48	0.37	0.42	0.45	0.49	0.61
WRFG future						
Mean	18.99	33.83	30.6	44.23	18.38	28.57
SD	8.66	9.47	8.6	34.28	8.94	17.89
CV	0.46	0.28	0.28	0.77	0.49	0.63

Table App.1.2 Yields of crops under all climate scenarios with no N loading restriction

Yields of Crops Baseline (Mg/ha)						
Ensemble history	Alfalfa	Corn	Soybean	Wheat	Pasture	Rye cover
Mean	9.04	8.26	1.89	5.75	1.18	6.54
SD	1.96	0.32	0.16	1.55	1.88	1.81
CV	0.22	0.04	0.09	0.27	1.60	0.28
Ensemble future						
Mean	9.55	7.06	1.93	3.99	1.33	3.05
SD	2.47	0.46	0.59	0.67	2.02	0.49
CV	0.26	0.07	0.30	0.17	1.52	0.16
CRCM history						
Mean	9.23	7.85	1.80	5.37	1.14	6.67
SD	2.13	0.65	0.27	1.85	1.78	2.54
CV	0.23	0.08	0.15	0.34	1.56	0.38
CRCM future						
Mean	8.95	6.69	1.83	3.82	1.36	3.86
SD	2.36	0.88	0.62	1.04	2.20	1.70
CV	0.26	0.13	0.34	0.27	1.61	0.44
WRFG history						
Mean	8.90	8.63	2.01	6.05	1.14	7.15
SD	2.20	0.61	0.21	1.82	1.88	2.00
CV	0.25	0.07	0.11	0.30	1.65	0.28
WRFG future						
Mean	9.97	7.08	1.87	4.04	1.21	3.63
SD	2.7	1.11	0.62	0.87	2.04	1.71
CV	0.27	0.16	0.33	0.21	1.69	0.47

Table App.1.3 Total gross margins, N loading levels and agricultural production with no constraint on N loading

	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
Total Gross Margin ($)	375,660	319,180	348,350	293,430	390,290	315,730
Total N Loading (kg)	15679	12671	15642	12924	15384	11867
Annual Crop Area (ha)[a]						
Corn Grain	211	208	211	179	212	210
Corn Silage	20	23	20	22	19	21
Full Season Soybean	9	157	36	186	17	158
Double Crop Soybean	147	0	120	0	140	0
Wheat	147	0	120	0	140	0
Alfalfa	9	8	9	8	8	8
Alfalfa Establishment	4	4	4	4	4	4
CRP	0	0	0	0	0	0
Pasture	20	20	20	20	20	20
Idle Land	3	3	3	3	3	3
Livestock						
Dairy Cows	80	80	80	80	80	80
Broiler Houses	1	1	1	1	1	1

[a] Total land area may not add to 423 ha due to rounding and crop rotation.

Table App.1.4 Total gross margins, N loading levels and agricultural production with a 25% N loading reduction constraint and uniform allocations of BMPs

	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
Total Gross Margin ($)	368,930	315,020	343,020	290,280	382,950	314,350
Total Gross Margin Baseline ($)	375,660	319,180	348,350	293,430	390,290	315,730
Cost of N loading constraint ($)[a]	6,730	4,160	5,330	3,150	7,340	1,380
Total N Loading (kg)	11,759	11,759	11,732	11,732	11,538	11,538
Total N Loading Baseline (kg)	15,679	12,671	15,642	12,924	15,384	11,867
Annual Crop Area (ha)[b]						
Corn Grain	211	171	211	165	212	210
Corn Silage	20	22	20	22	19	21
Full Season Soybean	126	168	156	162	126	145
Double Crop Soybean	31	0	0	0	31	0
Wheat	31	0	0	0	31	0
Alfalfa	8	8	9	8	8	8
Alfalfa Establishment	4	4	4	4	4	4
CRP	0	26	0	38	0	12
Pasture	20	20	20	20	20	20
Idle Land	3	4	3	3	3	3
Livestock						
Dairy Cows	80	80	80	80	80	80
Broiler Houses	1	1	1	1	1	1

[a] Cost = total gross margin baseline minus total gross margin under constraint.
[b] Total land area may not add to 423 ha due to rounding and crop rotation.

Table App.1.5 Total gross margins, N loading levels and agricultural production with 25% N loading reduction constraint under spatial targeting

	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
Total Gross Margin ($)	370,950	316,550	344,830	291,620	384,920	314,810
Total Gross Margin Baseline ($)	375,660	319,180	348,350	293,430	390,290	315,730
Cost of N loading constraint ($)[a]	4,710	2,630	3,520	1,810	5,370	920
Total N Loading (kg)	11759	11759	11732	11732	11538	11538
Total N Loading Baseline (kg)	15,679	12,671	15,642	12,924	15,384	11,867
Annual Crop Area (ha)[b]						
Corn Grain	211	195	211	165	212	210
Corn Silage	20	23	20	22	19	21
Full Season Soybean	126	141	136	163	127	146
Double Crop Soybean	31	0	20	0	30	0
Wheat	31	0	20	0	30	0
Alfalfa	8	8	9	8	8	8
Alfalfa Establishment	4	4	5	4	4	4
CRP	0	29	0	37	0	11
Pasture	20	20	20	20	20	20
Idle Land	3	3	3	3	3	3
Livestock						
Dairy Cows	80	80	80	80	80	80
Broiler Houses	1	1	1	1	1	1

[a] Cost = total gross margin baseline minus total gross margin under constraint.
[b] Total land area may not add to 423 ha due to rounding.

Table App.1.6 TGMs and costs ($) of N reduction and gains from targeting for the baseline and 25% N reduction goal

	Uniform application					
	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
TGM baseline	375,660	319,180	348,350	293,430	390,290	315,730
TGM 25% reduction	368,930	315,020	343,020	290,280	382,950	314,350
Costs 25% reduction	6,730	4,160	5,330	3,150	7,340	1,380
	Targeting method					
	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
TGM baseline	375,660	319,180	348,350	293,430	390,290	315,730
TGM 25% reduction	370,950	316,550	344830	291,620	384,920	314,810
Costs 25% reduction	4,710	2,630	3,520	1,810	5,370	920
Gains from targeting[a]	2,020	1,530	1,810	1,340	1,970	460
	30%	37%	34%	43%	27%	33%

[a] Gains estimated as the reduction in costs under targeting relative to uniform placement for a given percentage reduction in N loadings. Percentage gains from targeting = (gain from targeting/cost of uniform placement)*100

Table App.1.7 BMPs under uniform and targeting strategies

	Ensemble history	Ensemble future	CRCM history	CRCM future	WRFG history	WRFG future
25% loading reduction, uniform application						
No tillage (ha)	431	374	400	362	431	388
Cover crop wheat (ha)	31	0	0	0	31	0
Land retirement (CRP)	0	26	0	38	0	12
25% loading reduction, targeted application						
No tillage (ha)	431	371	420	363	430	389
Cover crop wheat (ha)	31	0	20	0	30	0
Land retirement (CRP)	0	29	0	37	0	11

Table App.1.8 BMP distribution with targeting in each TI class and a 25% N loading reduction constraint under different climate scenarios

BMPs application with targeting methods under Ensemble history										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	51	40	40	40	40	40	60
Cover Crop Wheat	0	0	0	11	0	0	0	0	0	20
BMPs application with targeting methods under Ensemble future										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	40	40	40	40	40	40	11
CRP	0	0	0	0	0	0	0	0	0	29
BMPs application with targeting methods under CRCM history										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	40	40	60	40	40	40	40
Cover Crop Wheat	0	0	0	0	0	20	0	0	0	0
BMPs application with targeting methods under CRCM future										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	40	40	40	40	40	40	3
CRP	0	0	0	0	0	0	0	0	0	37
BMPs application with targeting methods under WRFG history										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	50	40	40	40	40	40	60
Cover Crop Wheat	0	0	0	10	0	0	0	0	0	20
BMPs application with targeting methods under WRFG future										
BMPs	TI 1	TI 2	TI 3	TI 4	TI 5	TI 6	TI 7	TI 8	TI 9	TI 10
No Tillage	40	40	40	40	40	40	40	40	40	29
CRP	0	0	0	0	0	0	0	0	0	11

Chapter 2 Reducing Costs of Mitigating Nitrogen Loadings by Within- and Cross-county Targeting

2.1 Introduction

Nonpoint source (NPS) water pollution from agricultural production has raised public concern since the Clean Water Act was authorized in 1972. The National Water Quality Assessment reports that agricultural NPS pollution is the leading contributor to water pollution problems, including surveyed surface water, ground water, wetlands and estuaries (US EPA, 2017). The Chesapeake Bay, the largest estuary in United States, has suffered excessive nitrogen (N), phosphorus (P) and sediment loadings from several sources including intensive agricultural activities in the Chesapeake Bay watershed over the last few decades (US EPA, 2017). To mitigate this problem, the United States Environmental Protection Agency (US EPA) set up the Chesapeake Bay Total Maximum Daily Load (TMDL) in 2010 (US EPA, 2016). Based on 2018 N loading level for each state within the Chesapeake Bay watershed, Delaware, Maryland, New York, Pennsylvania, Virginia and West Virginia need to implement 37%, 10%, 18%, 35%, 11% and 1% N reduction respectively by 2025 (Chesapeake Bay Program, 2019).

Policymakers and program managers require estimates of the effectiveness and costs of programs to achieve water quality goals. Integrated optimization and simulation models, combining estimated hydrological processes and economic performance, have been used to predict costs of water quality control (Johansson and Randall, 2003; Secchi et al., 2007; Uthes et al., 2010; Rabotyagov et al., 2010; Kaufman et al., 2014; Xu et al., 2019).

A common finding from studies based on integrated economic-hydrological models is that costs can be reduced by spatial targeting of water quality improvement practices, also called Best Managements Practices (BMPs). Johansson and Randall (2003) compared estimated P abatement costs using targeting based on a P index and using a decision model based on abatement cost functions estimated at the national level. Their analysis was applied to watersheds at the eight-digit hydrologic level, covering 540,000-km^2 of agricultural land with a goal of mitigating P discharge from agricultural production. The results of the study show that average costs are \$20.63/kg for a total 64,464,656 kg P reduction and \$23.67/kg for a total 56,181,737 kg P reduction under targeting strategies based on marginal P abatement cost and the P index, respectively, given a \$1.3 billion budget. Secchi et al. (2007) estimated the total costs of achieving water quality improvement from the hypothetical placements of a selected combination of BMPs for 13 major Iowa watersheds covering 87% of the area of the state. They combined Soil and Water Assessment Tool (SWAT) with economic models, land use data, and BMPs, and found that depending on spatial placement the simulated effectiveness of the identical BMPs in reducing N, P, and sediment varies from 28% to 59%, 6% to 20% and 6% to 65%, respectively. Rabotyagov et al. (2010) developed an integrated simulation-optimization model to assess the optimal trade-off between nutrient loadings and the marginal abatement costs for a total of 35.53-km^2 cropland area in Squaw Creek watershed, Iowa. Kaufman et al. (2014) disaggregated the entire Chesapeake Bay watershed into statewide levels and carried out targeting of BMPs by state to minimize the N reduction costs (BMP implementation and maintenance costs) over the entire study area, using the Chesapeake Bay Watershed Model to estimate BMP effectiveness. Their results show that significant cost saving (60%) could be realized through targeting of BMPs.

Xu et al. (2019) evaluated the effects of climate change on potential farm-level cost savings from spatial targeting of water quality BMPs based on soil and terrain properties for WE-38 (7.3 km^2), a sub-watershed of Mahantango Creek Watershed in east-central Pennsylvania, which drains to the Susquehanna River. Their study found that compared with uniform BMP placement to reduce N loadings by 25%, targeting methods could reduce costs of achieving the same overall reduction by an average of 30% under three historical climate scenarios and an average of 38% under three corresponding future climate scenarios.

The above studies provide insight into optimal strategies to achieve water quality goals and illustrate the tradeoffs involved in the choice of scale of analysis. Studies conducted at a smaller scale can derive detailed agricultural production and BMP selection strategies (Rabotyagov et al., 2010; Xu et al., 2019). However, results from a small study area may provide limited information for regional or national-scale policy setting. Other studies have been conducted at a larger scale with regional level input data (Johansson and Randall, 2003; Secchi et al., 2007; Kaufman et al., 2014). Such studies may fail to account for the heterogeneity of farms across large study areas and the boundaries that limit farms' abilities to respond to water quality constraints and goals. For example, Kaufman et al. (2014) divided their study area into six representative farms aggregated at the state level. Such aggregation may lead to biased estimates of pollutant reduction costs because farms within a state may differ in their costs of responding to water quality goals and constraints.

To be useful to policymakers, costs and effectiveness of BMPs need to be aggregated to a large watershed or regional scale while retaining the variability in responses based on heterogeneous farm conditions across the study area. This study analyzes the benefits of targeting water quality practices in a large watershed while still considering farm heterogeneity that is characteristic of small-scale studies. We use the county or portion of county contained in the watershed as the assumed farm boundary. However, variability of physical resources within the county is also considered in the same way that farms are made up of fields with varying physical characteristics. We evaluate potential cost reductions from targeting water quality practices across counties as well as within-counties. We develop an integrated decision-making framework, incorporating economic optimization using a model formulated in GAMS (General Algebraic Modeling System) (GAMS Development Corporation, 2013 https://www.gams.com/) and a watershed scale model developed for the Susquehanna watershed (Wagena and Easton, 2018). We treat each county as a representative farm with differentiated soil types within the county and optimize the placement of BMPs, land retirement, and other N control actions within and across counties within a large watershed.

2.2 Models and input data

2.2.1 Study area

We carried out the study in the Susquehanna River basin, which contributes more than 50% of the freshwater to the Chesapeake Bay (Wagena and Easton, 2018). The total drainage area is approximately 71,000 km^2 and has six major subbasins: Chemung, Juniata, Lower Susquehanna, Middle Susquehanna, Upper Susquehanna and West Branch Susquehanna, covering portions of three states: Pennsylvania, Maryland and New York. Sixty-six counties are entirely or partially located in the watershed. The land use of the Susquehanna River basin includes 2% for water and wetland, 7% urban area, 21% agricultural land, 69% forest and 1% for other use (Susquehanna River Basin Commission, 2015). Only agricultural land is considered in this study; all other landuses, such as forest, are excluded. Since 76% of the Susquehanna watershed is located in Pennsylvania, we use the N reduction goal of Pennsylvania, 35%, as the regional N reduction goal in this study (Susquehanna River Basin Commission, 2016).

The area of crop and pasture within each county in the watershed is considered as a representative mixed crop and livestock farm. For those counties partially located within the Susquehanna watershed, we calculate first the percentage of each county's area within the watershed and then adjust the county level data on crop and pasture area accordingly. For example, 51.4% of Adams County PA is located within the Susquehanna watershed. Thus, we multiply 51.4% by all Adams County level data, such as cropland area and pasture and animal units.

2.2.2 Hydrological Model and Data

We use Soil and Water Assessment Tool – Variable Source Area (SWAT-VSA) model to estimate the N loading and crop yields for each county in this study. SWAT is a process-based, watershed-scale model that uses inputs of weather, soil, land cover and land management data to simulate surface and subsurface hydrology and various chemical and sediment fluxes (Arnold et al., 1998). In SWAT, the watershed is delineated into Hydrological Response Units (HRUs), the smallest spatial on which calculations are performed. An HRU is the total area in a sub-basin with the same land use, soil and slope. The SWAT-VSA model is a derivative of the SWAT model, which identifies areas of the landscape subject to variable source area of runoff (Easton et al, 2008, Collick, et al. 2015). In SWAT-VSA the area of each HRU is defined by the coincidence of land use and TI class. In SWAT-VSA, runoff depth within a TI class will be the same irrespective of land use while N dynamics vary with land uses and, thus, can differ within TI classes. In this study, there are a total of 10 TI classes covering the entire study area. Soil TI class 1 defines areas of the landscape least runoff prone and TI class 10 are the areas most runoff prone (Easton et al., 2008). For each county, crop yields and N loadings are determined by its unique combination and proportion within each of the 10 TI classes.

Crop yields and N loading levels by crops are generated by SWAT-VSA. Tables 2.1 and 2.2 show the summary of crop yields and N loading levels averaged over the 10 soil TI classes. Figure 2.1 presents the distribution of TI classes for the Susquehanna watershed with county boundaries.

Nitrogen delivery ratios are used to estimate the proportion of N leaving the field that reaches the Chesapeake Bay. The delivery ratio is based on three components: (i) the proportion of N generated by the agricultural land that reaches surface water (land to water); (ii) the part of N remaining in free-flowing streams and reaching the river (stream to river); (iii) the proportion of N delivered from river to the bay (river to bay). Hence, the N delivery ratio is calculated by multiplying land to water, stream to river, and river to bay N delivery ratios provided by CAST (Chesapeake Bay Program, 2019). Nitrogen delivery ratios are specified for land-river segments, which are the intersections of land segments (counties) and river segments (watersheds). Delivery ratios were established in the Phase 6 Model for the Chesapeake bay watershed and are obtained from the Chesapeake Assessment Scenario Tool (CAST) (Chesapeake Bay Program, 2019). We estimated the county-level delivery ratio by averaging the delivery ratios for land-river segments contained in that county, which vary from 0 to 1. Figure 2.2 shows the distribution of county-level delivery ratios in the Susquehanna watershed.

2.2.3 Economic Model Assumptions

The economic model consists of two parts. The first part incorporates the agricultural producer's perspective. The producer faces constraints on N loadings imposed by water quality programs and attempts to minimize the cost of meeting those constraints for the county-level representative farm. The second part incorporates the perspective of the water quality program manager. The watershed manager attempts to allocate pollution reduction goals across counties in order to minimize the watershed's aggregate costs of meeting a given goal for reducing N pollution. We assume that agricultural producers are price takers and that the water quality program manager has perfect information regarding N control costs, for example, true self-reporting by each county.

2.2.4 Economic model for within-county profit maximization

First, we consider the producer's perspective using county boundaries to represent a farm. Each county has its predominant enterprises, size, and physical conditions, including terrain, soil, and distance from fields to streams as well as its unique optimal combination of enterprises to maximize profit. As a result of such heterogeneity, the marginal N abatement cost (MNAC) curves differ by counties.

The producer's objective is to maximize expected net revenue $E_i(x)$ for county *i*:

$$Max\ E_i(x) = \sum_{c=1}^{C} \sum_{m=1}^{M} \pi_{cmi} * x_{cmi} + \sum_{l=1}^{L} \pi_{li} * x_{li} \quad (1)$$

Let π_{cmi} denote per unit net revenue from crop *c* in soil wetness TI class *m* and π_{li} denote per unit net revenue from livestock type l of county i. x_{cmi} and x_{li} are decision variables for the crop production area in soil TI class *m* for crop *c* and livestock production units for livestock type *l* of county *i*.

The expected county-level net revenue is maximized subject to constraints of county i. For crop production, the constraints for county i include conventional resource constraints and the nutrient requirements of crop production.

$a_{cmik} * x_{cmik} \leq b_{cmik}$ (2)

Equation (2) describes conventional resource constraints, including land area for crop production, crop rotation requirements, and machinery for crops; a_{cmik} denotes the amount of constraint k required per unit of county i in soil TI class m and b_{cmik} denotes the amount available of constraint k for crop c for county i in soil TI class m.

$p_{cmir} * x_{cmir} \geq w_{cmir}$ (3)

Equation (3) describes the nutrient (N, P, and potassium (K)) requirements of crop production, where p_{cmir} denotes the amount of nutrient r applied per unit area for crop c in soil TI class m and w_{cmir} is the total requirement of nutrient r for crop c in county i in soil TI class m.

For livestock production, the constraints for county i includes the livestock production resource constraints including the feed requirement.

$f_{lij} * x_{lij} \leq s_{lij}$ (4)

Equation (4) is a set of livestock production constraints including livestock facilities. f_{lij} denotes the amount of constraint j required per unit of livestock l and s_{lij} denotes the total amount of available facility j for livestock l.

$e_{liu} * x_{liu} \geq q_{liu}$ (5)

Equation (5) is the livestock feed requirement. e_{liu} is the per unit requirement of feed type u for livestock l; and q_{liu} is the total feeding requirement of livestock l for the *uth* feed type.

The above is the county-level profit maximization problem for each county in the watershed. Therefore, the total expected profit *A* from agricultural production generated by *n* counties in this watershed when there is no water quality constraint is

$A = \sum_{i=1}^{N} E_i(x)$ (6)

2.2.5 Economic model for watershed-level cost minimization

For the water quality program manager, the objective is to minimize the total marginal N abatement cost (MNAC) of the entire watershed under the given regional environmental goal. The objective is minimized by allocating different water quality goals, g_i, to each county within the watershed according to their MNACs. For a given N abatement constraint, the marginal abatement cost of each county is equal to the reduced net income with the N abatement constraint relative to TGM of each county under the baseline. The water quality manager is assumed to know the MNAC of each county located within the watershed which is denoted as $f'(\mathrm{x}_i)$, where x_i is the required N reduction for each county. Hence, the water quality manager's problem can be expressed as:

Min $\mathrm{TMC} = \sum_{i=1}^{N} f'(\mathrm{x}_i)$ (7)

subject to the regional environmental N reduction goal at the outlet G_e,

$\sum_{i=1}^{N} \omega_i \mathrm{x}_i \geq G_e$ (8)

$0 \leq \mathrm{x}_i \leq U_i$ (9)

where TMC is the total regional MNAC at the outlet; ω_i is the N delivery factor for county *i;* and U_i is the baseline N generated by county *i* under the county-level profit maximization.

Total abatement costs are minimized by allocating the N reduction goal among counties where the MNACs at the outlet are equalized across counties. Counties'

MNACs at the outlet equal MNACs at the edge of field divided by the delivery ratio, that is

$$\text{MNAC}_{outlet_i} = \frac{\text{MNAC}_{edge-of-field_i}}{\omega_i},\ i = 1, \dots, I \quad (10).$$

To implement the conceptual model we use linear programming in GAMS using the following steps:

1. We run the county-level model without N constraints to determine the baseline agricultural production, N loading, and county net revenues. The baseline results reflect the optimal agricultural production strategy of each county when there is no regional water quality goal.

2. The curve representing each county's MNAC at the outlet is generated based on the reduction in its net revenue with the N loading restriction relative to the baseline results. Each county's MNAC is derived based on targeting N reductions within the county. The heterogeneity in MNAC curves among counties, contributed by the variation in N delivery ratios, physical conditions and the pattern of agricultural production of each county, indicates the potential to reduce costs of achieving the watershed N reduction goal by targeting.

3. We minimize costs of achieving the regional water quality goal by minimizing the sum of all counties MNACs based on the results of step 2. Because of the step-wise nature of the MNAC curves, the equilibrium MNAC is close, but not exactly the same among counties.

4. We rerun the farm level model and assign N reduction goals for each county to get the corresponding production strategy to achieve the regional water quality goal.

5. We estimate the benefits of targeting as the reduction in costs of

achieving the regional water quality goal when reductions are based on different targeting scenarios compared to costs when equal percentage N reductions are assigned uniformly.

2.2.6 Quantifying benefits of within-county targeting

The benefits of within-county targeting are estimated based on the reduction of costs to meet the regional N reduction goal compared to the costs with uniform allocation of BMPs within the county. The benefits of within-county targeting are evaluated for both the cross-county targeting strategy (within county uniform, cross county targeting) and the cross-county uniform strategy (within county uniform, cross county uniform). Benefits of within-county targeting are evaluated with respect to placement of two BMPs: nutrient management (NM) and Conservation Reserve Program (CRP) lands. These BMPs are flexible and can be allocated to cropland anywhere. The remaining BMPs investigated in this study: off-stream livestock watering, prescribed grazing, grass buffer for cropland, cover crop and conservation tillage, have natural location constraints--existing pastures for prescribed grazing, adjacent to the stream for grass buffer, and existing pasture and adjacent to the stream for off-stream watering, and incorporated into the crop rotation for cover crop and conservation tillage. Here the within-county uniform strategy means each county applies NM and CRP uniformly over all agricultural land, each TI class getting its allocation of CRP and NM according to its corresponding proportion of the county's cropland. Crops are still allocated to TI classes based on profitability reflecting the assumption that agricultural producers know the soil productivity of their lands and allocate crops accordingly. Our model follows this crop selection behavior, putting crops in their most profitable TI classes to realize the objective of profit maximization.

Four strategies to meet the regional water quality goal are examined:

1. within-uniform-cross-uniform (WUCU): within-county uniform application of CRP and NM to soil TI classes, regional N reduction goal assigned uniformly across counties;
2. within-uniform-cross-targeting (WUCT): within-county uniform application of CRP and NM to soil TI classes, regional N reduction goal targeted across counties based on each county's MNAC;
3. within-targeting-cross-uniform (WTCU): within-county targeting of CRP and NM based on profitability, regional N reduction goal assigned uniformly across counties;
4. within-targeting-cross-targeting (WTCT): within-county targeting of CRP and NM based on profitability, regional N reduction goal targeted across counties based on each county's MNAC. The cost under the WUCU targeting method serves as the baseline to be compared with the other three strategies for achieving regional N reduction goal.

2.2.7 BMPs

Seven of the most effective BMPs for N reduction in the Chesapeake Bay watershed are considered in this study. They are conservation tillage, 10-meter width stream buffers, cover crops, crop NM, off-stream watering without fencing for livestock, prescribed grazing and land retirement (Chesapeake Bay Foundation, 2015; Kaufman et al., 2014). N reduction efficiencies and costs of BMPs are obtained from CAST (Chesapeake Bay Program, 2019). Table App. 2.1 in the supplementary material summarizes the average efficiency and costs of BMPs over all counties within the Susquehanna watershed. When detailed county-level efficiencies and costs of BMPs are available (Tables App. 2.2 and App. 2.3), that information is used instead of average values presented in Table App. 2.1.

Conservation tillage applied in this study is continuous no till, which reduces soil erosion and N runoff (Carpenter et al., 1998). Cover crops improve the soil structure and hence prevent N runoff (Ritter et al., 1998). Non-harvested rye and commodity wheat serve as cover crops. Non-harvested rye can follow full season soybean and corn. Commodity wheat can follow corn and is followed by double-cropped soybean.

Crop NM directs application of nutrients to crops at the right rate, time, and place to mitigate N runoff to the Bay (Chesapeake Bay Program, 2015). Two types of NM, with manure and without manure, are considered here (Chesapeake Bay Program, 2015, 2019; Nutrient Management Expert Panel, 2015).

Planting buffers along streams has been widely proven as an effective way to reduce nutrient loadings entering the waterway (Azzaino et al., 2002). We consider grass buffers with 10-meter widths in this study. The allowable buffer area of the entire Susquehanna watershed is calculated by GIS by building 10-meter width buffer areas around all streams for agricultural lands within the watershed. The estimated maximum potential buffer area within each county is based on stream frontage within agricultural lands in the county.

Off-stream watering without fencing for pastured livestock encourages livestock to stay out of streams for drinking, resulting in less pollution of the waterway. The maximum area that can be treated by off-stream watering is equal to the pasture area of each county.

Prescribed grazing (PG) utilizes a range of pasture management and grazing techniques to improve the quality and quantity of the forages grown on pastures and reduces the impact of animal travel lanes, animal concentration areas or other degraded areas (Chesapeake Bay Program. 2019). The maximum area that can be treated by PG is equal to the pasture area of each county.

The last BMP included in this study is land retirement under the Conservation Reserve Program (CRP). Land retirement reduces N runoff by taking the cropland on highly erodible soil out of agricultural activities and placing it in conserving uses such as grasses, shrubs, and/or trees. Landowners, who successfully enroll in this program, receive a rental payment for their retired land. In this study, the rental payment is based on CRP payment rate of each county in 2018 dollars (Table App. 2.3) (USDA FSA, 2018). The maximum allowable land that can be retired is 25% of total cropland of the county (NSAC, 2016).

2.2.8 Crop and livestock data

The Susquehanna watershed covers parts of three states, Pennsylvania, New York and Maryland, and includes all or part of 66 counties (Susquehanna River Basin Commission, 2016). The study area includes these 66 counties, with each considered as a representative farm with differentiated soil TI classes and integrated crop and livestock production.

The crops considered are the major crops in the three states comprising the watershed, including corn for grain, corn for silage, soybean, wheat, alfalfa, and pasture (USDA, 2014). Crop rotation patterns include continuous corn, continuous grass pasture, one-year corn one-year soybean, two-year corn three-year alfalfa, one-year corn two-year alfalfa, corn followed by double-cropped wheat and soybeans, and corn or soybean followed by rye cover. Crop prices/Mg (2018$) for corn grain, corn silage, soybean, wheat, and alfalfa hay are $249, $60, $499, $262, and $198, respectively. Crop costs/ha (2018$) excluding land rent and fertilizer costs for corn grain, corn silage, full season soybean, rye cover crop, double crop wheat/soybean, alfalfa hay establishment, and alfalfa hay are $967, $1,467, $495, $87, $1,029, $720, and $805, respectively (Penn State, 2015; Bosch et al., 2018). The model calculates fertilizer costs separately depending on nutrient source. Crop nutrient sources include commercial fertilizers, legume N carryover, and manure (Penn State, 2015). Total available cropland in each county is obtained from 2012 Census of Agriculture (USDA, 2014).

For livestock production, we consider both confined and pastured animals that are typically raised in the Susquehanna watershed, including beef cow-calf, dairy cows, hogs (farrow to finish), broilers, layers and turkeys. All hogs, broilers, layers and turkeys are assumed to be fed in confinement. For pastured animals, the grazing density is 3.2 cows per ha (Penn State Extension, 2016). All beef cows and calves are assumed to be pastured. For dairy cows, we assume only lactating cows are confined and dry dairy cows and dairy heifers are pastured. For a herd with 100 dairy cows, there are 40 bred heifers, 43 open heifers , and 47 yearling heifers for replacement (Virginia Cooperative Extension, 2011). Hence, the ratio between lactating cows and replacement heifers is 1:1.3 in the model. Livestock budget data are obtained from Penn State Extension (Penn State Extension, 2016), University of Maryland Extension (University of Maryland, 2011) and Virginia Cooperative Extension (Virginia Cooperative Extension, 2011). The unit gross revenues (2018$) for dairy cattle, beef cow-calf and hogs (farrow to finish, sold at 280lbs) are $4,128, $844, $174, respectively. Per bird gross revenues of layer and turkey are $42 and $29, respectively. Broiler revenues are $0.30 per bird, based on integrator payments to growers. The livestock unit costs (2018$) excluding land rent and farm raised feed are $2,272, $407, $0.07, $58, $24 and $27 for dairy cattle, beef cow-calf, broiler, hogs, layer and turkey respectively (Penn State Extension, 2016 for dairy cattle, layer, turkey and hog; UMD extension, 2011 for broiler; Virginia Cooperative Extension, 2011 for beef cow-calf). Livestock facility limits for each county within the study area are obtained from CAST under 2012 scenario (Chesapeake Bay Program, 2019). The feed requirements for dairy cattle, beef cow-calf and hogs follow 2011 Virginia Farm Business Management Livestock Budgets (Virginia Cooperative Extension, 2011). The feed for broiler, layer and turkey are supplied by the poultry integrator. Livestock budgets are provided in the supplementary material (Table App. 2.4).

The annual manure production from confined animal production includes 14.27 thousand liter (l) per dairy cow, 5.96 Mg per hog for breeding, 1.24 Mg per hog for slaughter, 0.001 Mg per broiler, 0.031 Mg per layer and 0.005 Mg per turkey (Chesapeake Bay Program, 2019). Sale prices for these manures are $-0.002/liter for liquid manure (the farmer is assumed to give the manure away and pay spreading costs), zero for solid manure from hog for breeding and hog for slaughter due to their relatively low nutrient content and high transportation costs, $14 per Mg for broiler and layer litter, and $21 for turkey litter (Bosch et al., 2018; Carreira et al., 2007). All prices and costs are adjusted to 2018 price level. The N runoff generated from pastured animals is estimated by SWAT-VSA (Table 2.2).

2.3 Results

2.3.1 Costs for achieving N reduction goal

First, we present the results of the baseline scenario, under which each county produces at the optimal level without the N reduction constraint. Next, we present the results of four strategies to meet the goal of 35% N reduction at the outlet relative to the baseline scenario.

When there is no N constraint, the total gross margin (TGM) over the entire watershed is $2,247,818,647 with $1,420,599,342 from livestock and $827,219,305 from 1,012,432 ha crop production (Table 2.3). Crop revenue here does not include the value of crops fed to livestock since the value of crops for feed is counted as feed costs for livestock production in the model. The aggregated N loading level at the edge of field for counties and the total N loading level at the outlet are 11,585,539 kg and 7,720,463 kg respectively. Two BMPs are selected: 1,012,432 ha of no tillage and 75,036 ha CRP under the baseline scenario. No tillage is more profitable than conventional tillage. A positive CRP area indicates that crop returns from some areas are lower than CRP payments even when there is no N reduction requirement. All cropland within the watershed is under crop production, pasture, or CRP. When there is no N constraint, corn grain and soybean are two major crops selected by the model because of their profits, followed by corn silage and alfalfa while 161,794 ha pastureland are selected for livestock production.

For a regional 35% N reduction goal, the allowable annual N loading level at the outlet is 7,720,463 kg * 0.65 = 5,018,301 kg. To achieve the regional 35% N reduction goal, the within-uniform-cross-uniform (WUCU) strategy incurs the highest cost: $184,493,267. Under this strategy the TGM decreases to $2,063,325,379, an 8% decrease compared with the baseline TGM (Table 2.3). The aggregated N loading level at the edge of field for counties and the total N loading level at the outlet are 7,530,601 kg and 5,018,301 kg, respectively. The crop production area decreases by 33% to 677,945 ha while total revenues from livestock production decrease to $1,403,877,918. Compared with the baseline scenario, corn grain area decreases 37%, which is the largest reduction among crops, followed by soybean, 34%. The reduced crop area is primarily replaced by an increase in CRP, which expands by over 250%. For BMP application, there are a total of 677,945 ha no tillage, 3,637 ha cover crop rye, 205,723 ha NM with manure, 242,054 ha NM without manure, 70,774 ha off-stream watering without fencing, 35,668 ha prescribed grazing and 269,547 ha CRP (Table 2.4). Buffers are not selected.

The within-uniform-cross-targeting (WUCT) strategy incurs the second highest cost, $159,699,178, to meet the 35% reduction in N delivered to the outlet. The cost represents a 13% cost saving relative to WUCU. For WUCT which applies CRP and NM uniformly within county, the gains from cross-county targeting are mostly contributed by county heterogeneities in terms of delivery ratios and agricultural production patterns. The cost savings due to cross county targeting result from increased crop production area (Table 2.3) and decreased BMP applications (Table 2.4) except for no tillage and NM (Table 2.4). Total crop production area increases from 677,945 ha under (WUCU) to 761,161 ha under (WUCT) (Table 2.3). The areas of cover crop rye, off-stream watering without fencing, prescribed grazing and CRP decline by 11%, 67%, 75% and 21%, respectively (Table 2.4) while areas with no tillage and NM with and without manure increase by 12%, 12% and 4%, respectively. The increase in no tillage and NM is due to more land being planted in crops than under the WUCU case.

The within-targeting-cross-uniform (WTCU) strategy has the third highest cost of meeting the 35% N reduction, $127,073,156, which is a 31% reduction compared to WUCU. The cost reduction is partly due to the increased crop production area, which increased from 677,945 ha under WUCU to 786,059 ha. The increased crop area relative to WUCU results in increases in no tillage from 677,945 ha to 786,059 ha (16%), NM with manure from 205,723 to 389,578 ha (89%) and NM without manure from 242,054 to 387,146 ha (60%). CRP increases slightly from 269,547 ha to 271,378 ha, cover crop rye decreases from 3,637 ha to zero. For BMPs for pastured animals, off-stream watering without fencing decreases from 70,774 ha to 24,044 ha; and prescribed grazing slightly increases from 35,668 ha to 39,665 ha. The gains from the within-county targeting method relative to uniform application (WUCU) are a result of targeting CRP and NM based on soil TI classes. The strategy allows each county to enroll land with lower marginal value for crop production and higher N runoff potential into CRP and apply NM on land with higher marginal value for crop production and relatively higher N runoff potential. This leads to a more than 73% increase in NM and a 31% total cost saving for the regional water quality goal compared with WUCU.

The within-targeting-cross-targeting (WTCT) strategy achieves the highest TGM, $2,130,533,853, among four strategies when there is a 35% N reduction goal. The cost is $117,284,794, a 36% reduction compared to the WUCU strategy. These savings result from the highest total crop production among the N reduction strategies, eliminating cover crop rye, and reducing off-stream watering without fencing by over 56,000 ha (80%), prescribed grazing by over 26,000 ha (74%) and CRP levels by over 50,000 (19%) ha with targeting. Crop areas are larger under WTCT compared to WUCU except for corn silage (Table 2.3). For example, some 63,000 ha more corn grain is produced with WTCT. Corn grain has the highest profit and generates the highest N loading level per ha among crops. No tillage and total NM (with and without manure) are higher under targeting reflecting higher overall crop production under WTCT compared to WUCU (Table 2.4). Cost reductions under WTCT are contributed by targeting NM and CRP based on soil TI classes within county and assigning N reductions across counties based on the MNAC curve. Both the unique physical conditions--the delivery ratio and the proportion of land with higher productivity, and unique agricultural production patterns--proportion of revenue from pastured livestock production, contribute to differences in MNACs for counties within the watershed.

Counties assigned the highest goals tend to have relatively lower MNACs at the outlet, which are contributed by relatively high delivery ratios and low MNACs at the edge of field (Equation 10 and Figure 2.3). MNAC at the edge of field for a county is affected by the distribution of soil TI classes and agricultural production patterns. A larger proportion of higher (wetter) TI classes raises MNAC because higher TI classes tend to have higher crop yields. Counties with somewhat higher corn and soybean yields will be assigned lower N reduction goals since these two crops bring highest net revenues among all crops considered in the model (Figure 2.4). Counties with the highest goals assigned tended to have somewhat smaller revenues from pastured livestock (Figure 2.3). Raising the proportion of revenues a county obtains from pastured livestock raises its MNAC as pasture BMPs--off-stream watering without fencing and prescribed grazing, are costly relative to their effectiveness (Table App. 2.1). While pastured livestock production contributes to high N reduction costs; confined livestock production does not. N runoff from confined animal manure disposal can be managed with nutrient management which is more cost effective compared to pasture BMPs (Table App. 2.1). Further layer, turkey and broiler litter can be sold for relatively high prices.

Ignoring either physical conditions affecting pollution potential or agricultural production patterns affecting economic productivity will lead to economically inefficient allocations of N reductions. For example, considering physical conditions by putting CRP on cropland with high pollution potential but ignoring economic productivity and therefore the opportunity costs to retire this land will reduce profit and raise the MNAC if other areas can reduce pollution by an equivalent amount at lower opportunity cost.

2.3.2 Discussion

Consistent with previous studies advocating spatial targeting based on soil criteria to reduce costs of meeting water quality goals (Carpentier et al., 1998; Secchi et al., 2007; Kaufman et al., 2014; Xu et al., 2019), our results show that the strategy of targeting reductions within and among counties is superior to the uniform strategy in terms of lowering costs to achieve a given water quality goal.

By disaggregating the watershed into county-level representative farms, we account for heterogeneity in production conditions and constraints within the watershed. For example, the CRP enrollment is limited to a maximum area of 25% cropland at a county level (NSAC, 2016). Ignoring the constraints imposed by farm boundaries, approximated here by county boundaries, may cause N abatement costs to be under-estimated.

Counter to previous studies, which applied a targeting method based on the soil criteria (Jha et al., 2010; Uthes et al., 2010; Willis and Privette, 2017), the cross-county targeting criteria in this study employing a MNAC curve, reflects physical conditions including the delivery ratio and agricultural production characteristics of counties within the watershed. Figure 2.5 summarizes the result of the allocation of N reduction goals under the WTCT strategy. For example, Herkimer County, NY, with a baseline N loading level of 15,956 kg and 18.4% of the N load reaching the outlet, receives the goal of zero due to its high marginal cost to reduce one kg of N at the outlet. Total costs for meeting regional N reduction goal will be lower if more reduction is assigned to other counties with higher N delivery ratios. Allegany County, NY, with 35.7% N delivery ratio to the outlet, is also not required to reduce any amount of N because its main agricultural production activity is livestock production (41% net revenues from pastured livestock production), which leads to the high MNAC at the edge of field. Furthermore, the relatively low delivery ratio of this county implies a high MNAC. Among all counties, Schuylkill County, PA receives the highest N reduction goal, 75%. Two factors contribute to this result. First, 100% of the N from Schuylkill County will reach the outlet. Given the 100% delivery ratio of Schuylkill County any N reduction efforts will be completely realized at the outlet, implying the MNAC at the edge of field is the same as that at the outlet. Second, MNAC at the edge of field is relatively low due to less dependence of revenues on livestock production (12% net revenues come from livestock production).

Within each county, this study targets the agricultural production and BMP placement based on the soil TI classes, and therefore represents a more comprehensive inter- and intra- county targeting comparison compared to previous literature (Carpentier et al., 1998). These findings illustrate that although there are large potential gains from targeting practices among counties—allocative efficiency (Abler and Shortle, 1991) within farm targeting of practices is even more important.

Results of this study highlight some policy implications for the Susquehanna watershed. Differentiated performance goals are necessary for allocating loading reductions efficiently within and among counties and promoting regional cost-effectiveness (Carpentier et al., 1998; Shortle et al., 2012). To achieve efficiency in allocating N reductions, policy makers should place greater emphasis on targeting BMPs through subsidies and technical assistance to counties with lower costs to meet N reduction goals. For the Susquehanna watershed, heterogeneity of physical conditions (soil TI class and delivery ratio) and agricultural production patterns (crop and livestock combinations) both contribute to the large differences of the marginal cost curves among counties and the potential to increase economic efficiency by targeting.

2.4 Summary

In this study, we assume policymakers are seeking to reduce N loadings by 35% to the outlet of the Susquehanna watershed. Agriculture plays an important role in achieving these reductions. The two-level targeting method applied in this study explores the possibility of lowering the costs to achieve these reductions by targeting reductions both among and within counties. Results of this study suggest that targeting methods should be considered at both within- and cross-county levels to increase cost-effectiveness of N reductions. To achieve the 35% N reduction goal at the watershed outlet, cross-county targeting, within-county targeting, and within- and cross-county targeting lower N abatement costs relative to uniform application by 13%, 31% and 36%, respectively.

Three limitations of our study should be mentioned. First, maximizing cost-effectiveness to meet the regional water quality goal is the only objective in this study. We do not consider equity for counties within the watershed as some counties do not need to reduce N loading, while the highest N reduction goal received by a county is 75%. However, given the voluntary nature of agricultural BMP adoption and the use of subsidies (cost-share and technical assistance) to encourage adoption, the policy implication of the study focuses on the optimal allocation of government subsidies to regions where they can be used most effectively. Second, we do not consider the transactions and information costs for the application of targeting, which may reduce the gains from targeting methods, which are based on compliance cost savings. Targeting may necessitate more information to determine which counties to target, which would increase costs. But Carpentier et al. (1998) showed that transaction and information costs could be lower under the targeting method compared with the uniform application because targeting methods place BMPs in ‘hot spots’ for nutrient loading and only information about such hot spots is needed. Further research, for example, quantifying the transaction costs to achieve targeting goals for within and cross county targeting will be needed to determine effects of transactions costs on feasibility of individual and regional level targeting methods. Third, we only consider effects of N loadings delivered to the outlet of the watershed and disregard local effects. For example, estimated N loadings at the edge of field under WTCT were some 550,000 kg larger than under WUCU (Table 2.3). Further research could attempt to estimate costs of local damages from these increased loadings and the effects of these costs on gains from targeting.

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Tables

Table 2.1 Crop yields (mg/ha)[a]

	Corn	Soybean	Wheat	Alfalfa	Rye [b]
Mean	4.86	3.18	5.04	9.75	4.84
SD	0.47	0.30	0.44	0.60	0.54
CV	0.10	0.09	0.09	0.06	0.11

[a] Values are means over TI classes and years (1981 to 2010)
[b] Rye is an unharvested cover crop in our model

Table 2.2 N loading level by crops (kg/ha)[a]

	Corn	Soybean	Wheat	Alfalfa	Rye	Pastured Dairy	Pastured Beef
Mean	9.61	6.60	8.76	4.72	5.32	20.88	30.91
SD	0.95	0.69	0.94	0.43	0.62	4.22	4.93
CV	0.10	0.10	0.11	0.09	0.12	0.20	0.16

[a] Values are means over TI classes and years (1981 to 2010)

Table 2.3 Farm revenues, costs, and production under the baseline and with the 35% N reduction goal

	Baseline	Within-Uniform-Cross-Uniform (WUCU)	Within-Uniform-Cross-Targeting (WUCT)	Within-Targeting-Cross-Uniform (WTCU)	Within-Targeting-Cross-Targeting (WTCT)
Total gross margin ($)	2,247,818,647	2,063,325,379	2,088,119,469	2,120,745,490	2,130,533,853
Cost of meeting regional 35% N reduction goal		184,493,267	159,699,178	127,073,156	117,284,794
N loading level at edge-of-field (kg)	11,585,539	7,530,601	8,085,637	7,530,601	8,085,637
N loading level at outlet (kg)	7,720,463	5,018,301	5,018,301	5,018,301	5,018,301
Total livestock revenue ($)	1,420,599,342	1,403,877,918	1,397,477,054	1,396,911,728	1,395,695,706
Dairy cattle revenue ($)	736,621,327	736,621,327	736,621,327	736,621,327	736,621,327
Broiler revenue ($)	41,705,787	41,705,787	41,705,787	41,705,787	41,705,787
Layer revenue ($)	512,297,838	512,297,838	512,297,838	512,297,838	512,297,838
Turkey revenue ($)	12,923,868	12,923,868	12,923,868	12,923,868	12,923,868
Beef cattle revenue ($)	117,050,522	100,329,099	93,928,235	93,362,909	92,146,887
Total crop revenue	827,219,305	659,447,461	690,642,414	723,833,762	734,838,146
Total cropland area (ha)	1,012,432	677,945	761,161	786,059	799,365
Corn grain	456,710	287,479	329,369	343,594	350,326
Corn silage	46,051	46,226	46,134	45,984	45,902
Soybean	495,851	326,799	368,593	382,676	389,319
Alfalfa	13,820	13,803	13,818	13,805	13,818
Rye Cover	0	3,637	3,248	0	0
Pasture	161,794	149,837	145,259	144,855	143,986
CRP	75,036	269,547	213,689	271,378	219,364

Table 2.4 Total BMP applications (ha) under uniform and targeting strategies to achieve the regional 35% N reduction goal

	Within-Uniform-Cross-Uniform (WUCU)	Within-Uniform-Cross-Targeting (WUCT)	Within-Targeting-Cross-Uniform (WTCU)	Within-Targeting-Cross-Targeting (WTCT)
No Tillage	677,945	761,161	786,059	799,365
Cover Crop	3,637	3,248	0	0
Nutrient Management with Manure	205,723	231,098	389,578	382,292
Nutrient Management without Manure	242,054	250,884	387,146	225,227
Grass Buffers	0	0	0	0
CRP	269,547	213,689	271,378	219,364
Off-stream Watering without Fencing	70,774	23,605	24,044	14,104
Prescribed Grazing	35,668	8,809	39,665	9,101

Figures

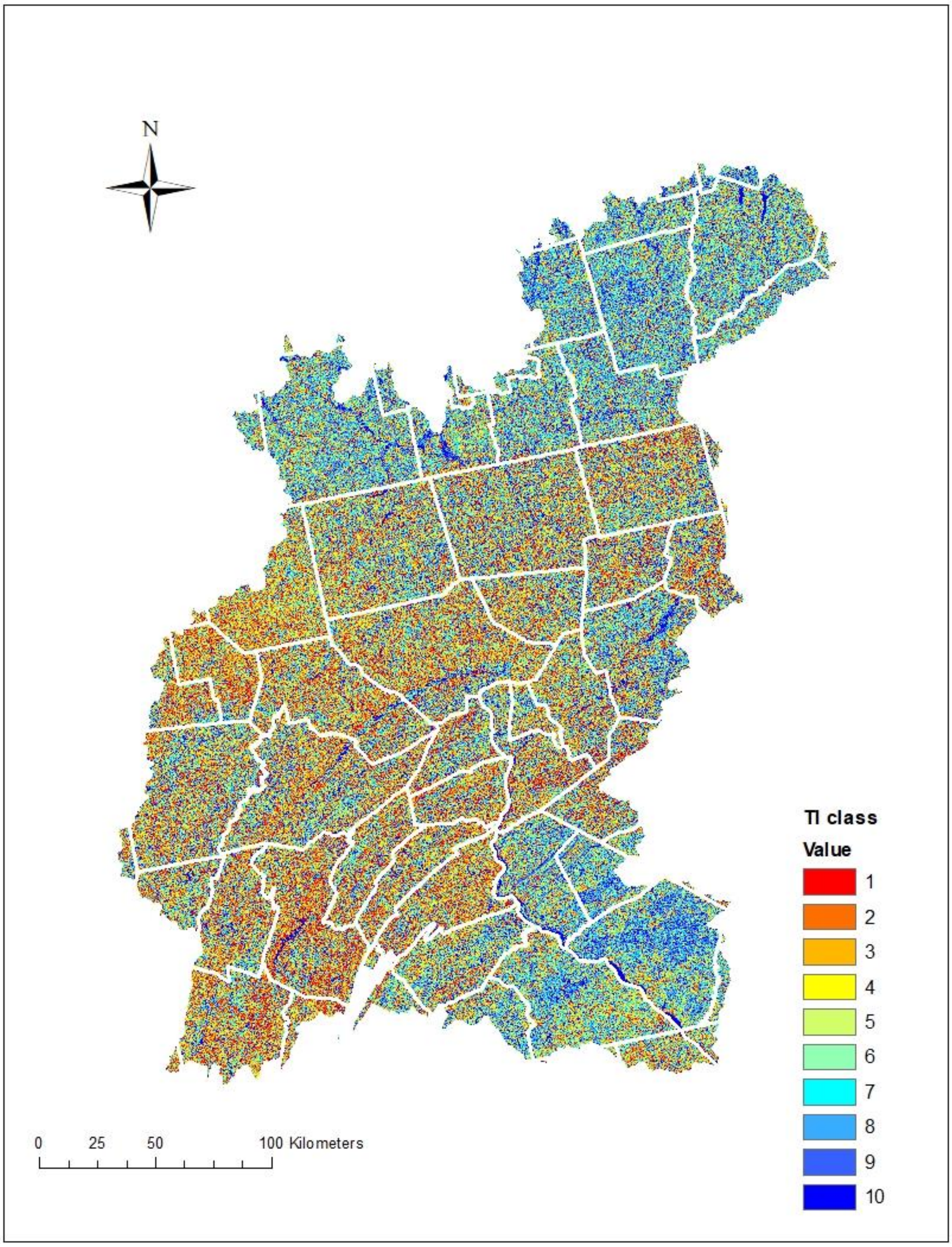

Figure 2.1 Distribution of TI classes by county (class 1 indicates least runoff prone and class 10 is most runoff prone)

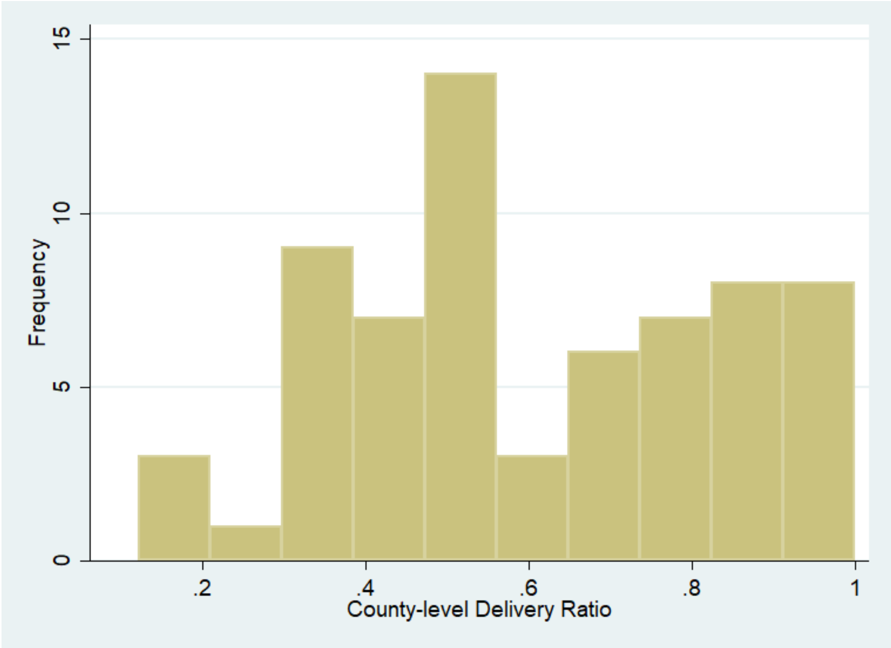

Figure 2.2 The frequency of county-level delivery ratios for Susquehanna watershed Counties (Observations=66)

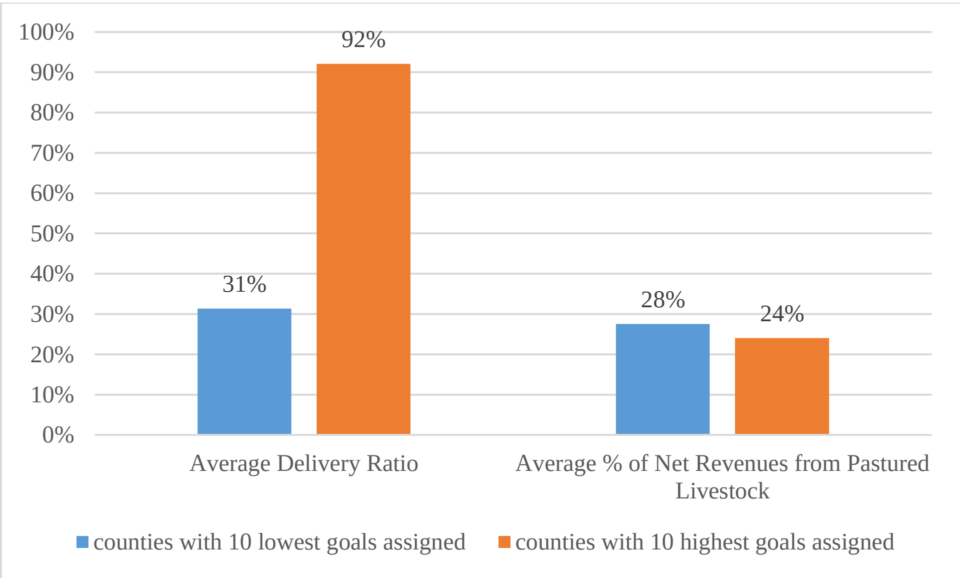

Figure 2.3 Characteristics of counties with lower and higher assigned N reduction goals

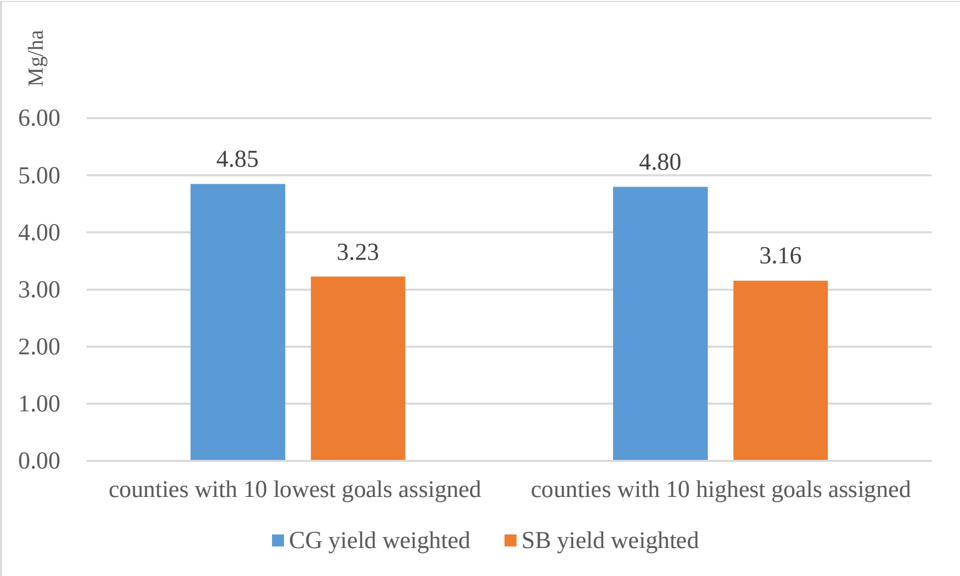

Figure 2.4 Weighted average of corn and soybean yields (mg/ha) for counties with lower and higher assigned N reduction goals

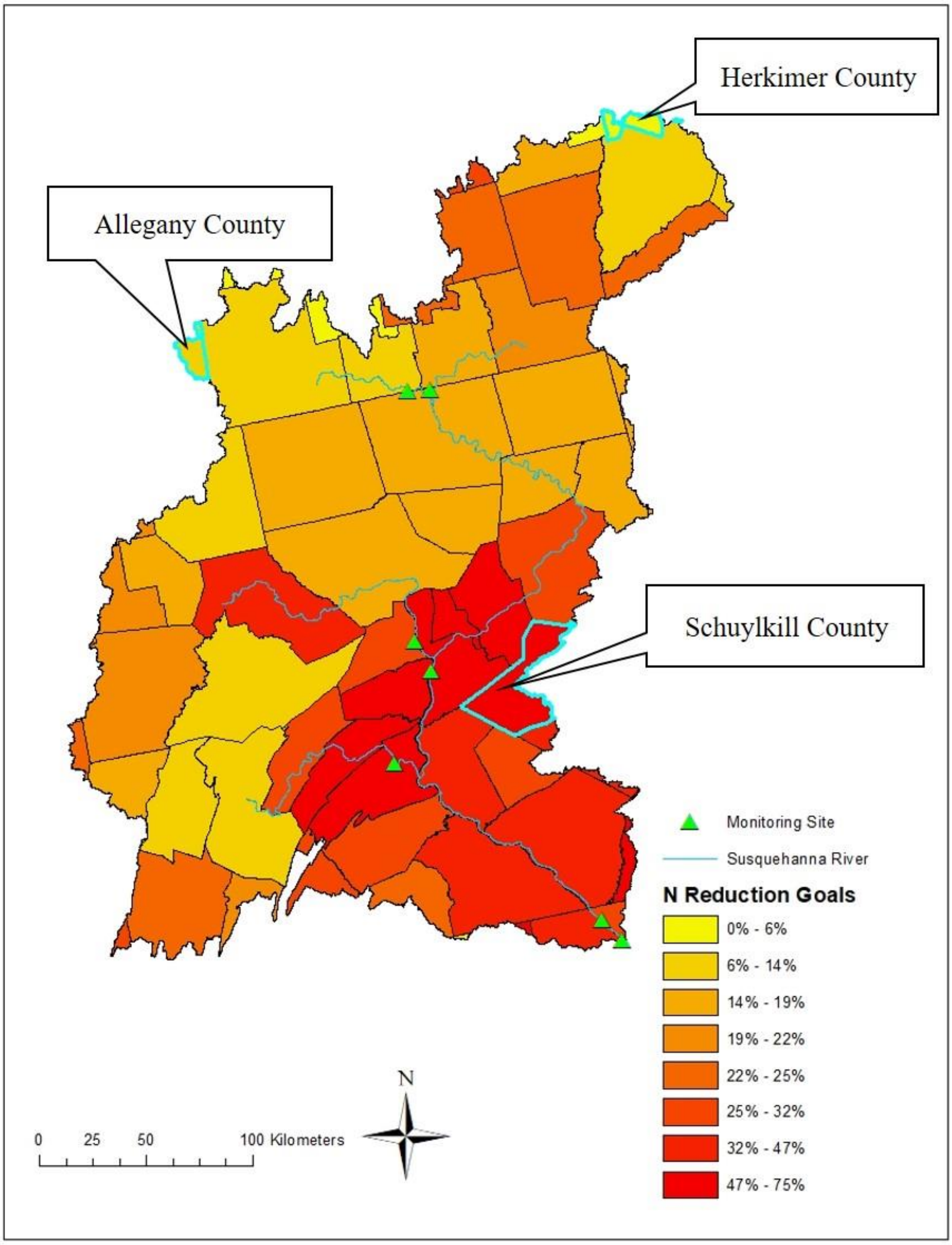

Figure 2.5 N Reductions allocated under within-targeting-cross-targeting method

Appendix tables

Table App 2.1 Average BMP efficiencies and costs over all counties[a]

BMPs	Average N loading reduction (%)	Average annualized cost/ ha (2018$)
Conservation tillage	10	-111
Stream buffers	37	495
Off-stream watering without fencing	5	73
Prescribed grazing	11	206
Rye cover crop [b]	-	-
Nutrient management with manure	27	44
Nutrient Management without manure	12	44
Land retirement (CRP)	100	268

[a] When county-level BMPs efficiency and cost data are available, that information is used instead of average values presented here. See Tables S2 and S3.
[b] N loading reductions from cover crops are estimated by SWAT-VSA and vary by soil and TI class. Commodity wheat is also a cover crop. Rye and/or wheat cover crop costs are included as part of the wheat-double cropped soybean rotation.

Table App. 2.2 Grass buffer efficiency by county [a]

County	State	Grass Buffer
Adams County	PA	0.61
Bedford County	PA	0.62
Berks County	PA	0.68
Blair County	PA	0.62
Bradford County	PA	0.62
Cambria County	PA	0.62
Cameron County	PA	0.62
Carbon County	PA	0.68
Centre County	PA	0.62
Chester County	PA	0.61
Clearfield County	PA	0.62
Clinton County	PA	0.62
Columbia County	PA	0.62
Cumberland County	PA	0.62
Dauphin County	PA	0.68
Elk County	PA	0.62
Franklin County	PA	0.68
Fulton County	PA	0.68
Huntingdon County	PA	0.68
Indiana County	PA	0.62
Jefferson County	PA	0.62
Juniata County	PA	0.68

Lackawanna County	PA	0.62
Lancaster County	PA	0.61
Lebanon County	PA	0.68
Luzerne County	PA	0.62
Lycoming County	PA	0.62
McKean County	PA	0.62
Mifflin County	PA	0.68
Montour County	PA	0.68
Northumberland County	PA	0.68
Perry County	PA	0.68
Potter County	PA	0.62
Schuylkill County	PA	0.68
Snyder County	PA	0.68
Somerset County	PA	0.62
Sullivan County	PA	0.62
Susquehanna County	PA	0.62
Tioga County	PA	0.62
Union County	PA	0.68
Wayne County	PA	0.62
Wyoming County	PA	0.62
York County	PA	0.68
Allegany County	NY	0.62
Broome County	NY	0.62
Chemung County	NY	0.62
Chenango County	NY	0.62
Cortland County	NY	0.62
Delaware County	NY	0.62
Herkimer County	NY	0.62
Livingston County	NY	0.62
Madison County	NY	0.62
Oneida County	NY	0.62
Onondaga County	NY	0.62
Ontario County	NY	0.62
Otsego County	NY	0.62
Schoharie County	NY	0.62
Schuyler County	NY	0.62
Stueben County	NY	0.62
Tioga County	NY	0.62
Tompkins County	NY	0.62
Yates County	NY	0.62
Baltimore County	MD	0.61
Carroll County	MD	0.61
Cecil County	MD	0.61

Harford County	MD	0.61

[a] CAST Source data (Chesapeake Bay Program, 2019); Values in this table are the remaining proportion of N loading after applying the grass buffer.

Table App. 2.3 BMPs costs/payments by county (2018$) [a]

County	State	Nutrient Management with & without Manure ($/ha)	Grass Buffer($/ha)	CRP Payment ($/ha)
Adams County	PA	40.94	527.87	329.81
Bedford County	PA	40.94	527.87	227.96
Berks County	PA	40.94	527.87	346.96
Blair County	PA	40.94	527.87	439.53
Bradford County	PA	40.94	527.87	285.35
Cambria County	PA	40.94	527.87	329.67
Cameron County	PA	40.94	527.87	375.43
Carbon County	PA	40.94	527.87	380.84
Centre County	PA	40.94	527.87	395.90
Chester County	PA	40.94	527.87	243.80
Clearfield County	PA	40.94	527.87	227.61
Clinton County	PA	40.94	527.87	332.96
Columbia County	PA	40.94	527.87	233.34
Cumberland County	PA	40.94	527.87	264.33
Dauphin County	PA	40.94	527.87	241.38
Elk County	PA	40.94	527.87	179.74
Franklin County	PA	40.94	527.87	270.20
Fulton County	PA	40.94	527.87	226.37
Huntingdon County	PA	40.94	527.87	437.16
Indiana County	PA	40.94	527.87	288.15
Jefferson County	PA	40.94	527.87	223.25
Juniata County	PA	40.94	527.87	241.81
Lackawanna County	PA	40.94	527.87	294.80
Lancaster County	PA	40.94	527.87	548.29
Lebanon County	PA	40.94	527.87	420.10
Luzerne County	PA	40.94	527.87	385.21
Lycoming County	PA	40.94	527.87	337.21
McKean County	PA	40.94	527.87	324.00
Mifflin County	PA	40.94	527.87	409.26
Montour County	PA	40.94	527.87	267.05
Northumberland County	PA	40.94	527.87	267.83
Perry County	PA	40.94	527.87	240.10
Potter County	PA	40.94	527.87	356.79
Schuylkill County	PA	40.94	527.87	262.34
Snyder County	PA	40.94	527.87	246.12
Somerset County	PA	40.94	527.87	196.74
Sullivan County	PA	40.94	527.87	257.94

Susquehanna County	PA	40.94	527.87	268.58
Tioga County	PA	40.94	527.87	276.04
Union County	PA	40.94	527.87	298.07
Wayne County	PA	40.94	527.87	313.91
Wyoming County	PA	40.94	527.87	265.37
York County	PA	40.94	527.87	341.90
Allegany County	NY	49.36	406.08	115.85
Broome County	NY	49.36	406.08	212.15
Chemung County	NY	49.36	406.08	104.43
Chenango County	NY	49.36	406.08	220.73
Cortland County	NY	49.36	406.08	183.03
Delaware County	NY	49.36	406.08	318.74
Herkimer County	NY	49.36	406.08	137.61
Livingston County	NY	49.36	406.08	155.11
Madison County	NY	49.36	406.08	168.61
Oneida County	NY	49.36	406.08	157.27
Onondaga County	NY	49.36	406.08	184.97
Ontario County	NY	49.36	406.08	147.39
Otsego County	NY	49.36	406.08	115.09
Schoharie County	NY	49.36	406.08	219.87
Schuyler County	NY	49.36	406.08	119.63
Stueben County	NY	49.36	406.08	127.38
Tioga County	NY	49.36	406.08	117.41
Tompkins County	NY	49.36	406.08	193.85
Yates County	NY	49.36	406.08	206.74
Baltimore County	MD	58.24	565.28	307.61
Carroll County	MD	58.24	565.28	388.96
Cecil County	MD	58.24	565.28	306.02
Harford County	MD	58.24	565.28	361.99

[a] CAST Source data (Chesapeake Bay Program, 2019).

Table App. 2.4 Livestock budget (2018 price level) [a]

	Gross revenue ($/unit)	Total costs ($/unit)	Net revenue ($/unit)
Dairy Cattle [b]	4,128	2,272	1,856
Beef Cow-calf [c]	844	407	437
Broiler [d]	0.3	0.07	0.23
Hog [b]	174	58	116
Layer [b]	42	24	18
Turkey [b]	29	27	2

[a] Gross revenue, total costs and net revenue are all adjusted to 2018 price level by multiplying their corresponding GDP deflators. See Bosch et al. (2018). Total costs exclude land rent and feed that can be raised or purchased and manure spreading.
[b] Penn State Extension, 2016
[c] Virginia Cooperative Extension, 2011
[d] University of Maryland Extension, 2011

Chapter 3 Selling Nutrient Reduction Credits under Uncertainty with Credit Banking

3.1 Introduction

Because of high rates of nutrient and sediment runoff leading to eutrophication and dead zones in the Chesapeake Bay, the U.S. Environmental Protection Agency (US EPA) set up the Total Maximum Daily Load (TMDL) to mitigate runoff in December 2010. The program aims to reduce 25% nitrogen (N), 24% phosphorus (P) and 20% sediment by 2025 relative to the loading level in 2010 (US EPA, 2016). One way of inducing agricultural sources to voluntarily reduce their emissions is through water quality trading (WQT). WQT has been viewed as a promising policy tool and is advocated by policy makers and government agencies because of its market-based criteria that could improve the cost-effectiveness of policies to achieve these water quality goals. WQT allows sources with high abatement costs to purchase credits from sources with relatively lower costs, which generates additional revenues for credit sellers while helping buyers meet their own caps with lower costs.

The agricultural sector, contributing 42% N loads and 54% P loads to the Chesapeake Bay and exempted from federal permitting for nutrient emission, is expected to participate in the WQT program and contribute reductions for improving water quality (Van Houtven et al., 2012). For WQT programs within the Chesapeake Bay watershed, landowners usually need to first achieve a baseline level of nutrient reduction through all required BMPs that are applicable to their agricultural operations and then they will be allowed to generate and sell nutrient credits to potential trading partners. Once the baseline level of nutrient mitigation is achieved, additional reductions realized by approved BMP enhancements or land conversion are eligible to generate nutrient credits for selling to buyers who generate nutrient runoff in the same tributary or watershed for the same calendar or compliance year (Branosky et al., 2011).

WQT creates another revenue source for agricultural producers from selling their earned nutrient credits and helps them realize cost savings from BMP application in the short term. However, farmers are often reluctant to participate in WQT program regardless of the direct financial incentive. One issue is the limited flexibility of selling nutrient credits, that is farmers cannot bank awarded nutrient credits to the next year; all unsold credits in this year will be zero next year regardless of future demand. For risk-averse agricultural producers , the market uncertainty, like the ambiguity about supply and demand within WQT markets, would discourage credit providers from entering the WQT markets (Walker and Selman, 2014). The inability to bank unsold credits means that farmers may not get full payment from the environmental services provided by them and cannot take advantage of fluctuations in credit prices since credit demand varies year by year. For example, under changeable climates, farmers may face extraordinary demand with high credit prices for some years and may not be able to sell all their credits for other years. These issues lead to further uncertainty about the profitability of participating in the WQT program. Hence, the prohibited credit banking reduces financial incentives for agricultural producers to participate in the WQT program.

To mitigate this inflexibility, EPA published the new water quality trading policy memorandum in February 2019, which identifies six market-based principles designed to encourage creativity and innovation in the development and implementation of programs that help to reduce pollutants in America’s waters (US EPA, 2019). One of these six principles is allowing water quality credits to be banked for future use.

There is extensive previous literature on the dynamics of the tradeable permits system with banking and decision making for various environmental and natural resources problems, such as air emission and groundwater trading. The air emission offsets program has achieved success in terms of the cost saving over command and control (Tietenberg, 2010). Cronshaw and Kruse (1996) develop a firm-level profit maximization model with a temporal setting of allowing permits banking and find that a firm would not bank permits unless the growth rate of permit price rises with the rate of interest. Kling and Rubin (1997) use an optimal control model to explore the incentive of firms for borrowing and banking emission permits for offsetting firms' own emissions or selling to other firms in the future. They find that when emission's permits can freely move intertemporally, firms will not choose the optimal levels of emissions and outputs, but produce more outputs and generate more emissions than optimal through borrowing permits to meet their emission caps in early periods and generate less emissions than optimal in later periods. Schennach (2000) analyzes the permit banking for electricity-generating units by building a framework that determines the length of the banking period, the absolute level of the emissions and the permit price. The framework also incorporates banking behavior under uncertainty about future marginal pollution abatement costs and the demand for electricity. Results show that emission permit banking could smooth the effect of the shock on the permit price level.

For groundwater extraction, Provencher and Burt (1994) investigate farmers' behavior regarding the use of annually assigned tradeable permits to the *in situ* groundwater stock through a dynamic programming framework with stochastic surface water deliveries. The tradeable permits represent the private groundwater stock of each farm. Permit trading changes the farm's activities of pumping water over time, increasing (decreasing) when they purchase (sell) the permits. The permit price could play a role in controlling the rate of groundwater pumping over time. Laukkanen and Koundouri (2006) explore the economic and environmental outcomes of the optimal individual and social extraction rates by the method of dynamic programming with stochastic rainfall. Results show that the individual optimal extraction rate exceeds the socially optimal rate and the competitive extraction leads to serious depletion of the aquifer and significant welfare losses for a small-capacity aquifer.

WQT is similar to tradeable permit system of air emission and groundwater extraction because participants have to sacrifice revenues to generate credits in all cases and intertemporal decision making is used for maximizing the present value. However, WQT differs from these two topics in three aspects. First, unlike the air emission trading market in which every participant has to be in compliance with the emission cap, and unlike the groundwater permit market in which farmers need the groundwater for crop production, nutrient credit suppliers (farmers) do not need to meet their water quality goal and hence banking nutrient credits for future use does not serve for smoothing the abatement cost curve across time periods. Second, the nutrient credits are obtained through applying eligible BMPs. The BMP installation cost for participating in the WQT program needs to be added into the individual's objective. Third, WQT markets are relatively thin since buyers and sellers are required to generate nutrient runoff to the same tributary or watershed. As a result, nutrient credit prices are usually determined by bilateral negotiation instead of by government agency (Woodward and Kaiser, 2002).

Transaction costs, which are inevitable in WQT markets, are considered in this study as well. Previous literature regarding the tradeable-permit system for pollution mitigation shows that the transaction cost should be incorporated into decision making for the trading implemented for WQT markets (Stavins, 1995; Hahn and Hester, 1989;

Woodward et al., 2002; DeBoe and Stephenson, 2016). Following Stavins (1995) and Stephenson and Shabman (2017), transaction costs involved in WQT for credit sellers can be identified as (i) pre-trading costs, including the administration costs associated with the certification, verification and registration for nutrient credits; (ii) costs associated with time and efforts for credits trading such as searching for potential buyers, bargaining during the negotiation process, and contracting costs to implement the trading agreements; (iii) post-trading transaction costs regarding monitoring and enforcement of BMP application in the agreement.

To explore these problems exclusively raised by WQT, this paper aims to examine farmers' credit-selling behavior and corresponding economic outcomes for WQT when credit banking is allowable, taking transaction costs into consideration. An optimal control framework with credit prices driven by a stochastic process in WQT markets is used for the analysis.

3.2 Theoretical Framework

Due to uncertain future demands for credits, the option to delay selling credits to the following time periods could be valuable. By delaying the time to sell nutrient credits, a credit owner can observe whether credit prices increase or decrease before making a selling decision. One assumption for the theoretical framework is that the nutrient credit price is taken as given by farmers since they do not have market power.

We develop the theoretical framework in two stages. In the first, we hold the BMP investment as given, and examine the farmer's behavior of credit sales with the possibility of credit banking. In the second, we allow her to choose an optimal BMP investment level for credit generation along with a path of credit sales when credit banking is allowed. For both stages, we examine the outcomes in both model variants taking into account transaction costs associated with credit banking and sales. Since nutrient credits here are term credits that are awarded annually, the BMP considered in this framework is for agricultural working land. There are total four scenarios will be discussed in the theoretical framework.

3.2.1 Dynamic optimization model for credits selling when banking is allowed with fixed BMP investment

We formulate a dynamic model to examine individual credit owner's decisions regarding credits selling and banking. We assume a farmer participating in a WQT program by investing fixed BMP level on working land and being awarded q credits each year over a T-year contract. The farmer aims to maximize her discounted profits from selling these credits. She can choose the amount of credits to sell in this time period and store the unsold credits to the next time period. The objective function for individuals' profit maximization problem at time t is

$$\underset{\mathrm{u(t)}}{\mathrm{Max}} \int_0^T \mathrm{p(t)}u(t)e^{-rt}dt \quad (1)$$

$$\mathrm{s.t.}\ \dot{A} = -u(t) + q, \quad (2)$$

$$\mathrm{A(0)} = A_0 = 0. \quad (3)$$

$\mathrm{u(t)}$ is the amount of sold credits at time t, given that the available credits are $\mathrm{A(t)}$; r is the interest rate, and $\mathrm{p(t)}$ is the unit price of credits. Equation (2) is the equation of motion when credit banking is allowed; equation (3) is the initial state of credit stock based on credits awarded from one-unit BMPs investment.

Credit price is assumed to be stochastic, driven by the demand for credits in WQT markets. Following Clarke and Reed (1989), the price is driven by stochastic processes with independent increments:

$$dp(t) = \alpha p(t)\mathrm{dt} + \sigma p(t)\mathrm{dw(t)}, \quad (4)$$

where α is the constant drift, σ is the constant volatility and w is the increment of a standard Wiener process, $\mathrm{w(t)} \sim \mathrm{N(0, t)}$. Following Kafash and Nadizadeh (2017), equation (4) could be analytically solved

$$\mathrm{p(t)} = p_0 e^{\left(\left(\alpha - \frac{1}{2}\sigma^2\right)\mathrm{t} + \sigma w(t)\right)}, \mathrm{p(0)} = p_0. \ (5)$$

The mean of the price is $E(p(t)) = p_0 e^{\alpha \mathrm{t}}$.

The Hamiltonian based on equation (1) to (3) could be written as:

$$\mathrm{H} = \mathrm{p(t)}u(t) + \lambda(\mathrm{t})[-u(t) + q]. \ (6)$$

The control variable, $u(t)$, is linear in the Hamiltonian. This implies a bang-bang solution in which the farmer sells credits either at the lower bound ($u(t) = 0$) or the upper bound ($u(t) = A(t)$) to maximize her objective function. That means the decision for banking and selling credits depend on the exogenous price fluctuation, which will be examined later in the empirical section.

The transaction cost function consists of parts (i), (ii) and (iii) mentioned in previous section. In previous literature, the transaction costs for WQT markets are usually defined in a linear way (DeBoe and Stephenson, 2016). The linear way is proper to represent the costs associated with the administration part, but trading and post-trading costs are likely to be nonlinear (part ii and iii). We split the transaction costs into two parts in this study. The first part, $C_1(A(t))$, assumed to be positively linear in credit stock, denotes the transactions costs for pre-trading (part i). Since transaction costs associated with credits generation are fixed over time given the same amount of credits awarded in each time period (part i) they are not considered here. $C_1(A(t))$ only accounts for the administration costs associated with credit banking. Because there is no existing banking policy for WQT markets, we base these transaction costs on a similar program, air emission trading program. The program requires that any person who wants to bank emission reductions should submit an application to the Air Pollution Control Officer, which involves fees for credit banking application, credit transfer application, credit reclassification application and an advisory opinion (Air Pollution Control District County of San Diego, 2019). We assume that the unsold and banked nutrient credits incur similar transaction costs to those of the air emission trading program, for which $C_1'\big(A(t)\big) > 0$ and for which $C_1''\big(A(t)\big) = 0$. $C_2(u(t))$, transaction costs associated with trading and post-trading (part ii and iii), is a function of credits sold, for which $C_2'\big(u(t)\big) > 0$ and for which $C_2''\big(u(t)\big) > 0$. The convexity of $C_2(u(t))$ comes from the fact that the more credits to be sold, the more searching and bargaining efforts will occur per unit of credit. In addition, the monitoring and enforcement costs (part iii) increase at an increasing rate with increasing BMP investment in working agricultural land (Rees and Stephenson, 2017). The problem could be expressed as

$$\underset{\mathrm{u(t)}}{\mathrm{Max}} \int_0^T \big[\mathrm{p(t)}u(t) - C_1\big(A(t)\big) - C_2(u(t))\big]e^{-rt}dt. \quad (7)$$

Equation (7) is subject to equation (2) and (3) as well. The Hamiltonian is:

$$\mathrm{H} = \big[\mathrm{p(t)}u(t) - C_1\big(A(t)\big) - C_2(u(t))\big] + \lambda(\mathrm{t})[-u(t) + q]. \quad (8)$$

The maximum principle for equation (8) implies the first-order conditions:

$$\frac{\partial \mathrm{H}}{\partial \mathrm{u(t)}} = p(t) - \frac{\partial C_2\big(u(t)\big)}{\partial u(t)} - \lambda(\mathrm{t}) = 0, \quad (9)$$

$$-\frac{\partial \mathrm{H}}{\partial \mathrm{A(t)}} = \frac{\partial C_1\big(A(t)\big)}{\partial A(t)} = \dot{\lambda}(\mathrm{t}) - r\lambda(\mathrm{t}), \qquad (10)$$

$$\frac{\partial \mathrm{H}}{\partial \lambda(\mathrm{t})} = -u(t) + q = \dot{A}. \qquad (11)$$

Rearrange equation (9) and we get:

$$\lambda(\mathrm{t}) = p(t) - \frac{\partial C_2\big(u(t)\big)}{\partial u(t)}. \quad (12)$$

From equation (12), the derivative of $\lambda(t)$ with respect to time can be written as

$$\dot{\lambda}(t) = \dot{p}(t) - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\frac{\partial u(t)}{\partial t} = \dot{p}(t) - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\dot{u}(t). \quad (13)$$

Putting equations (12) and (13) into (10), we get:

$$\frac{\partial C_1(A(t))}{\partial A(t)} = \dot{p}(t) - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\dot{u}(t) - r\left(p(t) - \frac{\partial C_2(u(t))}{\partial u(t)}\right). \quad (14)$$

Rearranging equation (14), we could get:

$$r = \frac{\dot{p}(t) - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\dot{u}(t) - \frac{\partial C_1(A(t))}{\partial A(t)}}{p(t) - \frac{\partial C_2(u(t))}{\partial u(t)}}. \quad (15)$$

Equation (15) is the equilibrium condition with transaction costs when nutrient credits can be banked for future use, conditional on the predetermined BMP investment. This result is an analogue of the Hotelling's rule. For the RHS of equation (15), the denominator is the net price for credit sales at time t; the numerator is the net price increase for credit sales over time, $(\dot{p}(t) - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\dot{u}(t))$, minus the marginal cost for holding credits, $(\frac{\partial C_1(A(t))}{\partial A(t)})$, which is the net price increase rate. In equilibrium, the LHS of equation (15), the interest rate, should equal the RHS of equation (15), the net price increase rate of nutrient credits. In equilibrium the farmer is indifferent between selling credits now versus waiting to sell them in a future period. If the net credit price increase rate is greater than the interest rate, the farmer can benefit from waiting to sell credits; if the interest rate is greater than the net credit price increase rate, the farmer will choose to sell all available credits and bank the revenues. $u(t) = u^*$ can be derived from equation (15).

3.2.2 Credit selling decision model when BMP investment is contingent on the credit-selling behavior

In this section, the BMP investment is endogenous. Consider a problem of a farmer who has met the threshold requirement of the WQT program and observed the potential profitability of participation. The first step for this farmer is to determine the level of BMP investment to generate nutrient reduction credits. The BMP investment involves costs for installment and maintenance. Hence, the BMP investment area depends on the trade-off between the expected NPV of revenues generated by nutrient credit selling and BMP investment costs. The problem for the farmer in the first step is to maximize her expected total revenues from selling credits over a T-year contract to determine the BMP investment level given the price information at $\mathrm{t} = 0$. For the second step, the farmer needs to determine the optimal timing of credit sales to maximize the NPV from credit sales over time.

WQT without transaction costs

We consider the case without transaction costs. The NPV of the expected profits to participate in the WQT program over a T-year contract at $\mathrm{t} = 0$ can be mathematically expressed as:

$$R(V_0) = E\int_0^T (f(l)p(t) - C(l))e^{-rt}dt = \int_0^T (f(l)E(p(t))) - C(l))e^{-rt}dt$$

$$= \int_0^T (f(l)p_0 e^{\alpha \mathrm{t}} - C(l))e^{-rt}dt = \int_0^T (f(l)p_0 e^{-(r-\alpha)t} - C(l)e^{-r\mathrm{T}})dt$$

$$= \frac{f(l)p_0(1 - e^{-(r-\alpha)\mathrm{T}})}{r - \alpha} - \frac{\mathrm{C}(l)(1 - e^{-r\mathrm{T}})}{r}, \qquad where\ p_0 > \underline{P}. \quad (16)$$

V_0 is the NPV of credit selling profits at time 0; $p(0) = p_0$ is the WQT credit price at time 0, which is assumed to be greater than the threshold for participation, $\underline{P}$. l is the

BMP investment level which needs to be determined. $f(l)$ is the total credits awarded annually to the farmer based on nutrient reduction at the edge of field and the expected quantity of credits sold for each time period at $\mathrm{t} = 0$. $f(l)$ is assumed to be concave, i.e. $f'(l) > 0$ and $f''(l) < 0$. The concavity comes from the fact that the more BMPs applied, the more nutrient runoff could be reduced, but the amount of nutrient reduction at the edge of field from one more unit of BMP application is decreasing when the soil runoff potential is heterogeneous within a farm. $C(l)$ is the cost function for BMP investment, which is assumed to be convex. If the expected credit selling revenue from extra BMP application, $f(l)E(p_t)$, is always greater than expected revenue from agricultural production without extra BMPs, a corner solution applies and the farmer will incorporate all her crop production with the BMP and vice versa. The farmer's BMP application level with the goal of NPV maximization at $\mathrm{t} = 0$ could be specified as

$$\max_{l} R(V_0) = \frac{f(l)p_0(1 - e^{-(r-\alpha)\mathrm{T}})}{r - \alpha} - \frac{\mathrm{C}(l)(1 - e^{-r\mathrm{T}})}{r} \quad (17)$$

Taking the derivative with respect to l,

$$\frac{\partial R(V_0)}{\partial l} = \frac{f'(l)p_0(1 - e^{-(r-\alpha)\mathrm{T}})}{r - \alpha} - \frac{C'(l)(1 - e^{-r\mathrm{T}})}{r} = 0, \qquad (18)$$

$$\frac{f'(l^*)p_0(1 - e^{-(r-\alpha)\mathrm{T}})}{r - \alpha} = \frac{C'(l^*)(1 - e^{-r\mathrm{T}})}{r}. \qquad (19)$$

Equation (19) shows that in equilibrium the optimal BMP application level, l^*, occurs where the LHS of equation (19), the expected NPV obtained from applying one more unit BMP, equals the RHS of equation (19), the marginal nutrient abatement cost through BMP application. The BMP should be applied to lands with highest runoff potential first since nutrient reduction is largest and more credits will be awarded in these lands. The BMP will be applied until the marginal revenue generated by one more ha with BMPs equals the marginal BMP application cost.

After installing l^*-acres of BMP and obtaining $f(l^*)$ credits in each time period, the next step for the farmer is to determine the optimal selling path for these credits over a T-year contract with the allowance of storing the credits for future use. The credit selling problem over time can be written as

$$\max_{\mathrm{u(t)}} \int_0^T \mathrm{p(t)} u(t) e^{-rt} dt \qquad (20)$$

$$\mathrm{s.t.}\ \dot{A} = -u(t) + f(l^*), \quad (21)$$

$$\mathrm{A(0)} = A_0 = 0. \quad (22)$$

A_t is the stock of credits; A_0 is the initial level of the stock of credits.

The current value Hamiltonian is

$$\mathrm{H} = \mathrm{p(t)} u(t) + \lambda(\mathrm{t})[-u(t) + f(l^*)]. \quad (23)$$

Similar to case in which the BMP investment is fixed, when there are no transaction costs, the control variable, $u(t)$, is linear in the Hamiltonian. The bang-bang solution implies the farmer should sell either zero or $\mathrm{A(t)}$ in each time period to maximize profit.

WQT with transaction costs

When transaction costs are considered in the expected NPV for taking part in the WQT, the NPV of the expected profits to participate into the WQT program over T years can be expressed as

$$\mathrm{R}^T(V_0) = E\int_0^T [f(l)p_t - C(l) - C_2(f(l))]e^{-rt} dt$$

$$= \frac{f(l)p_0(1 - e^{-(r-\alpha)\mathrm{T}})}{r - \alpha}$$

$$- \frac{\big(C(l) + C_1(f(l)) + C_2(f(l))\big)(1 - e^{-r\mathrm{T}})}{r}. \quad (24)$$

The farmer's land allocation problem with the goal of NPV maximization at time 0 could be specified as

$$\max_{l} \mathrm{R}^{T}(V_0) = \frac{f(l)p_0(1-e^{-(r-\alpha)\mathrm{T}})}{r-\alpha} - \frac{\left(C(l)+C_2(f(l))\right)(1-e^{-r\mathrm{T}})}{r} \quad (25)$$

Taking the derivative with respect to l,

$$\frac{\partial \mathrm{R}^{T}(V_0)}{\partial l} = \frac{f'(l)p_0(1-e^{-(r-\alpha)\mathrm{T}})}{r-\alpha} - \frac{\left(C'(l)+C_2{}'\big(f(l)\big)\right)(1-e^{-r\mathrm{T}})}{r} = 0, (26)$$

$$\frac{f'(l'^{*})p_0(1-e^{-(r-\alpha)\mathrm{T}})}{r-\alpha} = \frac{\left(C'(l'^{*})+C_2{}'\big(f(l'^{*})\big)\right)(1-e^{-r\mathrm{T}})}{r}. \quad (27)$$

Equation (27) is the equilibrium condition for optimal area with BMP application, which shows that the last unit of land with BMP application should generate the same marginal net value as the marginal BMP application cost. Although we could not mathematically compare equation (27) with (19) since l appears on both sides of equations, the difference between equation (27) and (19) is obvious. The RHS of equation (27) now includes one additional cost term that capture the marginal transaction costs associated with an additional unit of land installed with BMP.

To determine the credit selling path after applying l'^{*} area of BMPs, the farmer faces the problem:

$$\underset{\mathrm{u(t)}}{\mathrm{Max}} \int_0^T \left[\mathrm{p(t)}u(t) - C_1\big(A(t)\big) - C_2(u(t))\right]e^{-rt}dt \quad (28)$$

$$\mathrm{s.t.}\ \dot{A} = -u(t) + f(l'^{*}), \quad (29)$$

$$\mathrm{A(0)} = A_0 = 0. \quad (30)$$

The current value Hamiltonian is

$$\mathrm{H} = \mathrm{p(t)}u(t) - C_1\big(A(t)\big) - C_2\big(u(t)\big) + \lambda\mathrm{(t)}[-u(t) + f(l'^{*})]. \quad (31)$$

Similar to the case of fixed BMP investment with transaction costs, we get:

$$r = \frac{\dot{p(t)} - \frac{\partial {C_2}^2(u(t))}{\partial (u(t))^2}\dot{u(t)} - \frac{\partial C_1(A(t))}{\partial A(t)}}{p(t) - \frac{\partial C_2(u(t))}{\partial u(t)}}. \quad (32)$$

Equation (32) is the equilibrium condition with transaction costs when nutrient credits can be banked, contingent on the BMP investment selected in the initial time period, which is the same as equation (15) in terms of the components in equations. We derive the optimal credit selling path for this case from equation (32), $\mathrm{u(t)} = u'^*$. Different from equation (15) where the BMP application is given, the magnitude of $\frac{\partial C_1(A(t))}{\partial A(t)}$ and $\frac{\partial C_2(u(t))}{\partial u(t)}$ in equation (32) are contingent on BMP application area selected in the first step and the awarded credits, l'^* and $f(l'^*)$. l'^* has a linear relationship with the given area of BMP application, but the awarded credits, $f(l'^*)$, have a nonlinear relationship with the nutrient credits awarded to the given BMP application level, q. Hence, the credit selling paths generated by equation (15) and (32) will not be precisely the same, but we expect the similar shape of these two credit-selling paths over time.

3.3 Application to the WQT markets in the State of Pennsylvania

3.3.1 Study area

In this section, we examine the results of our theoretical model for the WQT markets in the State of Pennsylvania. Based on 2018 N loading level, Pennsylvania still needs to reduce 35% N to meet the target loading level set up in 2010 by the Chesapeake Bay Total Maximum Daily Load (TMDL). The study area is Northumberland County, PA, located at the junction of the North and West Branches of the Susquehanna River and covering 1,236 km^2 area with 375 km^2 cropland and 57 km^2 pastureland (USDA, 2014). Northumberland County is selected for its intensive agricultural production, high delivery ratio (0.92) and large amounts of total nitrogen (approximately 3 million pounds annually) delivered to the Chesapeake Bay (Northumberland County Conservation District, 2014). We are modelling a representative typical farm within the Northumberland County as the study area. According to 2012 Census of Agriculture, the average farm size of Northumberland County is 62 ha, (USDA, 2014). The representative farm size is assumed to be 62 ha. The land constraint, soil distribution and other input data for the representative farm are the corresponding data of Northumberland County in 2012 Census of Agriculture proportionally reduced by 605 times (37,536/62=605). This farm is assumed to consist of 53 ha cropland and 9 ha pastureland corresponding to the ratio of total cropland and pastureland in the County of 37,536 ha and 5,706 ha, respectively.

3.3.2 Numerical simulation model

The numerical simulation model addresses the question of how the banking policy affects an individual farmer's returns from participating in Pennsylvania Nutrient Credit Trading Program (PANCT). The numerical simulation model is composed of a hydro-economic model and dynamic programming. We use an integrated hydro-economic model to simulate the edge-of-field N reduction generated by NM application, which consists of a process-based hydrological model and a static economic model. The hydrological model used for estimating the crop yields and N runoff potential for the study area is Soil and Water Assessment Tool- Variable Source Area (SWAT-VSA). SWAT is a process-based, watershed-scale, physical model that simulates surface and subsurface hydrology and various chemical and sediment fluxes (Arnold et al., 1998). SWAT-VSA is a derivative of the SWAT model, which identifies areas of the landscape subject to variable source area of runoff (Easton et al, 2008, Collick, et al. 2015). Wagena and Easton (2018) provide detailed hydrological model description and parameter calibration results for the study area. The economic model follows Xu et al. (2019, working paper), which is a static profit maximization model. Crops considered include corn, soybean and alfalfa. The prices and costs are showed in supplementary materials (Table App 3.1). Livestock includes dairy cattle, beef cattle, broiler, layer, turkey and hogs. Livestock budget for production is provided in Table App 3.2 in supplementary material. Dynamic programming is used for the intertemporal credit-selling decision for the farmer with backward recursion; the salvage value of available credits is set to be zero after the last time period. The simulation results will be compared with the no-banking situation to see the magnitude of banking impacts on an individual farmer's welfare. The simulation will also provide insight into the sensitivity of gains from credit banking to the theoretical model's parameters.

The PANCT allows existing municipal and industrial wastewater treatment plants (WWTPs) to achieve annually assigned nitrogen and phosphorus wasteload allocations (WLAs) through purchasing NPS credits (US EPA, 2012). After meeting the baseline requirement, farmers can generate credits by applying extra eligible BMPs and generating extra nutrient reduction beyond the baseline level. These extra nutrient reductions will be awarded as per kg based credits and farmers can sell the annually awarded credits to offset the discharge from WWTPs to the same watershed. The trading ratio is 1:1 between PS and NPS. There is a 10% reserve ratio for nutrient credits generated by NPS to address the uncertainty associated with NPS BMP efficiency (Branosky et al., 2011; Stavins, 2019). That is, if a farmer is awarded 100 kg nutrient credits annually, the total available credits to be sold are 90 kg.

The BMP used for generating credits for this study is nutrient management (NM). In Pennsylvania, cost-shared BMPs are eligible to generate nutrient credits (Branosky et al., 2011). The NM cost-sharing offered is \$18.3 per ha in 2018\$ (Tremplo County, WI, 2015). The per ha application costs for the farmer is \$40.9-\$18.3=\$22.6 for both NM with and without manure. The N reduction efficiencies of NM with and without manure are 27% and 12%, respectively (Chesapeake Bay Program, 2019).

Initial parameter values for the theoretical model are shown in in Table 3.1. The initial nutrient credit price for NM application is assumed to be determined through a bilateral negotiation with a spot contract, which is \$14/kg/year in \$2018 (Ribaudo and McCann, 2012). The transaction cost for pre-trading preparation is assumed to be linear in the credit stock, i.e. $C_1\big(A(t)\big) = dA(t),$ where $d > 0$. The transaction cost for selling credits, is assumed to be quadratic in sold credits, i.e. $C_2\big(u(t)\big) = bu(t) + cu(t)^2,$ where $b, c > 0$. Following Ribaudo and McCann (2012), pre-trading cost per kg N is \$0.22 in 2018\$, that is $d = 0.22$. We calibrate the parameters for $C_2\big(u(t)\big)$, based on the \$0.39 per kg N in 2018\$, that is $b = 0.37\ and\ c = 0.02$. Initial values of price drift and volatility (Table 1) used in the simulation are 0.01 and 0.01. Parameter values selected for nutrient prices are conservative since we want to avoid overstating the gains from banking, which will be varied to test sensitivity of total revenues to price fluctuation.

We simulate numerically the optimal N credit-selling path based on exogenous NM application first then the optimal nitrogen credit-selling path contingent on endogenous NM application. Both cases are solved with and without transaction costs. For each of these cases, we solve the system in discrete time with necessary and sufficient conditions for an optimum. Total revenues from four cases are all compared with their corresponding cases when N credits are not allowed for banking.

3.4 Results

3.4.1 Results for exogenous NM application

For exogenous NM application, we assume there is 110 kg N reduction could be generated at the edge-of-field of the representative farm each year; 110 kg N reduction are generated by 47 ha NM application from the hydro-economic model for the representative farm. For a 10% reserve ratio, there are total 99 kg N credits can be sold annually. The quantity for credit sold when credit banking is not allowed is at its profit maximized N credit level in each year. Total revenues achieved from the without banking case could be viewed as the upper bound that the farmer could expect (Table 3.2).

Table 3.2 presents the simulation results holding 47 ha NM application for with and without banking when the transaction costs are absent and present using the initial parameters from Table 1. When the transaction costs are not considered, the empirical results under credit banking case accord with the theoretical expectation for the bang-bang solution; the timing of sales aligns with the highest prices over the time period. Gains from banking policy are the difference of total revenues (no discounted) between with and without credit banking. With no transactions costs, a farmer with 110 kg N reduction at the edge of field generated by NM application could benefit from credit banking with $777 (5.23%) over a 10-year contract realized by credit selling. When transaction costs occur, the total revenues decrease to $12,569 and $12,534 for banking and no banking cases, respectively. Banking credits could bring $35 (0.28%) in total revenues from credit sales with transaction costs given 47 ha NM application.

3.4.2 Results for endogenous NM application

The results of exogenous NM application case show the effects of the transaction costs on the gains from credit banking when the farmer's NM investment decision at t = 0 is independent of NM application cost and transaction costs associated with WQT. The results from the endogenous NM application present the effects of NM application costs and transaction costs on the NM investment level and credit generated for participating the WQT program. Then the credit-selling path and the gains from banking, which are contingent on the NM application level invested at $t = 0$, are determined.

At $t = 0$, the N loading level without extra NM application is 692 kg N; the expected NPV of 10-year total revenues from agricultural production only is $ 648,127.

Table 3.3 presents the farmer's decision about NM application level for joining in the WQT program at $t = 0$. When the farmer does not consider transaction costs associated with WQT, 47 ha NM will be applied, which could decrease N runoff generated by the agricultural production at the edge-of-field from 692 kg to 582 kg. The farmer will be awarded 110 kg N credit each year for a 10-year contract. At $t = 0$, it is hard for the farmer to determine the quantity of credits to be banked in each time period and hence the expected credit sold in each time period is 110 kg N as well. The expected NPV over 10 years for agricultural products and N credit sales is $652,035, 0.6% higher than the expected NPV from agricultural production only for 10 years. When transaction costs are taken into consideration, the theoretical framework yields ambiguous results about the comparison of the BMP application level between with and without transaction costs because of the unknown magnitude of the transaction costs. Results of the numerical simulation show that the NM application level is reduced to 28 ha, a 40% decrease relative to the case without transaction costs. As a consequence, 28 ha NM area leads to the edge-of-field N loading level of 617 kg. The farmer will receive 75 kg N annually based on the baseline N loading level, 692 kg; the credit awarded is 32% lower than the case without transaction cost. The expected NPV from credit sales and agricultural production over 10 years is $650,380, improving the baseline NPV by $2,253 (0.35%).

Table 3.4 presents the simulation results about N credit selling when NM application is endogenous, where the paths of credit selling under the absence and presence of transaction costs are chosen to maximize the sum of total revenues to both cases. Banking N credit for future selling could increase total revenues by 5.23% and 0.33% compared with no banking for without and with transaction costs respectively.

3.4.3 Sensitivity Analysis

Because of limited data availability, most parameters in Table 1 are calibrated using limited nutrient credit trading information from the State of Pennsylvania. For example, the unit N credit price for WQT implemented by a bilateral negotiation over years is unavailable. As a result, the initial parameter values associated with price fluctuation are chosen with observation of a limited number of trades in Pennsylvania WQT markets (Table 1), which are known with uncertainty. Transaction costs, usually private information for credit brokers, are calibrated with limited information from previous study with unknown trading volume (Ribaudo and McCann, 2012). In addition, the magnitude of interest rate relative to the nutrient credit price increase rate is the key factor that affects the farmer's credit-selling decision in the theoretical framework. It is instructive to consider changes to the model parameters in order to gauge the effects of nutrient credit banking policy on an individual farmer's credit-selling behavior and economic outcome when facing price uncertainty. For this section, the sensitivity analysis is conducted based on the endogenous NM application case with transaction costs; the economic outcome derived by changed parameter values will be compared with its corresponding results when nutrient credit banking is not allowed.

The first important consideration is the fact that price fluctuations may be more stable or drastic relative to the initial parameter values selected for the stochastic price over time, which would alter the relative values of the parameter, α and σ. Table 3.5 and 3.6 describe the change in the path of credit selling when the price drift and volatility tends to be large. When price is extremely stable ($\alpha = 0$ in Table 3.5 and $\sigma = 0$ in Table 3.6), there is no gain for the farmer from credit banking since the credit-selling paths under both banking and no banking cases are exactly the same. The gains from banking relative to no banking in terms of the total revenues slightly increase with the increase in price drift. That is, when there is general economic growth which leads to increasing nutrient credit prices given low price volatility, farmers could benefit from banking credits for future sale, but the increase relative to the scenario that banking is not allowed is small. The gains from banking increase at an increasing rate with the increase in the price volatility (Table 3.6). Banking could protect the farmer's profitability and increase the total revenues of credits sales from higher price volatility. Figure 3.1 presents the impact of price volatility on the optimal credit banking and selling path under banking policy over time. The higher the price volatility, the more variation there is in the credit-selling path. The farmer will choose to bank credits when price is low to protect their profitability from credit sales.

The second necessary consideration is associated with parameters for transaction costs, which are calibrated given limited information. To see how transaction costs affect the NM application, credit creation and further the credit-selling path, we would alter the relative values of the quadratic parameter, c. Table 3.7 presents the impact of changing the trading transaction cost function on the farmer's decision in terms of the credit quantity generated by NM application. From the left column to the right in Table 3.7, with the increase in the quadratic parameter, the marginal transaction cost becomes steeper, leading to a more rapid growth in the transaction cost with less credits being sold. Expected NPV of the sum of agricultural production and credit sales for a 10-year contract decreases from 650,385 to 649,495 to 649,092; NM application level decreases as well since the marginal cost for N credit generation plus marginal trading cost needs to be equalized with the marginal revenue brought by N credit sales in equilibrium. Reduction in NM application level results in an increase in the N runoff level at the edge of the field and a decrease in credits awarded annually. Table 3.8 shows the impact of steeper transaction cost functions on changes in quantity of credits to be awarded in each time period and gains from banking. With the available credits sold going down, the total revenues and gains from banking both decrease at a decreasing rate.

The interest rate is the last parameter to be examined in this section. Our theoretical framework predicts that the magnitude of the interest rate relative to the nutrient credit price increase rate directly affects the farmer's credit selling and banking behavior. We alter the value of interest rate from 1%, 5%, 7% to 10% to measure its effects. Figure 3.2 shows that the credit-selling path will be flatter under a higher interest rate and banking credits will be more attractive under a lower interest rate, which is consistent with the theoretical prediction. Consider, when the interest rate is relatively lower than the potential price increase rate of nutrient credits, banking credits and waiting to sell them at a higher price increase rate could benefit farmers more. Similarly, when the interest rate is high, the incentive for banking credits will decrease. The farmer tends to sell credits as soon as possible to earn the interest rate in the bank and hence the credit-selling paths become flatter under higher interest rates in Figure 3.2.

3.5 Conclusions

We have examined the farmer's credit-selling behavior under a proposed policy that nutrient credits can be banked for future use in this study through a simple intertemporal model of the farmer's decision making when facing price uncertainty and considering transaction costs for credit banking and selling. Results of the model predict that the farmers will sell either zero or all available credits when the transaction costs are absent. When the transaction costs occur, the farmer will be indifferent between selling credits now versus waiting to sell them in a future time period when the interest rate equals the increase rate of nutrient credit price. Otherwise, the farmer will tend to sell credits as soon as possible or wait to sell them in a future time period when the interest rate is greater than or smaller than the nutrient credit price increase rate, respectively.

A numerical simulation calibrated using the example of WQT markets in the State of Pennsylvania through a representative farm located in Northumberland County, PA is applied to examine the results of our model. The simulation eliminates the ambiguity in the theoretical framework, for example, the BMP application level changes when transaction costs appear, validates the selling-path predicted in the model and also sheds light on understanding how banking policy could protect farmers' profitability from credit sales when facing price uncertainty. Results from the simulation and sensitivity analysis present that a higher price volatility implies a larger gain from banking relative to the no banking outcome; however, banking credit for future use because of higher price drift, which may be driven by the expected economic or population growth, increases revenues only slightly.

Transaction costs, an important hindrance for trading, are examined in the numerical simulation as well. Results indicate that transaction costs largely reduce the benefits from banking. For exogenous NM application, the presence of the transaction costs decreases the gains of banking credits from 5.23% to 0.28%; for endogenous NM application, the presence of transaction costs significantly reduces the NM application level decreases by 40%. This finding is consistent with previous literature that high transaction costs are currently the main factor that drive low participation from farmers to generate term nutrient credits through BMP application on agricultural working land (Rees and Stephenson, 2014). The reduction of NM application leads to decreasing credit generation, which further lessens the gains from banking. In our simulation, the total gains from banking are $30 from a 10-year time horizon planning with 75 kg credit awarded annually.

Relative to other environmental and natural resource trading system with banking allowance, for example, air emission and groundwater trading programs, WQT involves a much thinner market where participants face more restricted geographically constraints than other programs. For example, Virginia's Nutrient Credit Exchange Program requires that trading could only happen between credit sellers and buyers who generate the nutrient runoff to the same tributary; PANCT requires that trading can occur among sources within the same watershed (US EPA, 2007; US EPA, 2012). Based on the own characteristics of WQT markets, our results imply that this proposed credit banking policy will improve the participation from farmers in the WQT programs for three reasons. First, credit banking improves the flexibility of credit sales, for example, the unsold credits can be saved to the following time periods for sale, which ensures that the environmental services provided by farmers can be fully paid and profitability realized for joining in the WQT markets. Second, our results, which could be viewed as the farmer's expectation of this proposed policy, suggests that the larger gains could be brought by the higher nutrient credit price volatility. For WQT markets, we expect a high price volatility for nutrient credits in the future due to: (i) the price is generated by bilateral negotiation since there are only a limited number of credit buyers and sellers in the same market; (ii) the future climates are predicted to be wetter and there is increasing probability of extreme precipitation in northeastern United States, which will increase the demand for nutrient credits in WQT markets (Marquardt Collow et al., 2016; Woodward and Kaiser, 2002). For example, the nutrient credit supply in Pennsylvania was ample relative to the demand side prior to 2018; however, due to the extremely wet weather in 2018 resulting in excessive flows, flooding, and inflow and infiltration issues, the demand of WWTPs for nutrient credits is higher than usual, causing nutrient credit prices to soar (PA DEP, 2019). Hence, the farmer will expect this proposed policy could increase their revenues from credit sales directly and tend to participate in the WQT programs. Third, although we try not to overstate the gains from credit banking, for example, we choose conservative parameter values for price fluctuation and zero initial credit stock under banking case for comparing the total revenues under banking and no banking cases prudently, farmers could still benefit from credits banking. We also quantify the impact of transaction costs on gains from banking. One caution suggested by the results is, if credit banking involves relatively high transaction costs, they will easily offset the gains brought by the fluctuation in credit prices.

Three limitations should be mentioned here and can be extended in future study. First, the decision of credit sold with banking in each time period is derived by backward recursion, which could be viewed as a perfect forecast for decision making. For WQT in real life, participants may not achieve the gains relative to the no banking case estimated in this study, though credits are assumed to be sold out in each time period for no banking case, which is the upper bound revenue that could be achieved under no banking as well. Second, the farmer is assumed to be risk-neutral in our model. It would be interesting to see how banking policy affects risk-averse participants' trading behavior and corresponding economic outcome. When a farmer is risk-averse, the utility from credit sales will increase at a decreasing rate. Allowing credit banking for risk-averse farmers is expected to increase their utility more from banking than risk-neutral farmers. Third, the parameters in transaction cost functions are static in our model. Jaraite and Kažukauskas (2012) find that transaction costs play an important role in the initial years for the emission trading market and decline over time due to learning-by-doing. Based on the results in this study, if there are structural changes that reduce the transaction costs over time, the gains from credit banking are expected be enhanced further for farmers.

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Tables

Table 3.1 Initial parameter values for numerical simulation of the farmer's credit-selling behavior over time under banking and no banking

Parameter	Description	Initial value
T	Years for the contract	10
p_0	Nutrient credit price at t=0	14
α	Price drift of nutrient credits	0.01
σ	Price volatility of nutrient credits	0.01
d	Linear parameter for transaction cost function 1	0.22
b	Linear parameter for transaction cost function 2	0.37
c	Quadratic parameter for transaction cost function 2	0.02
r	Interest rate	0.07

Table 3.2 Simulation results, including credit-selling path and nondiscounted total revenues from credit sales for exogenous NM application

Time period		Exo. NM application w/o transaction costs		Exo. NM application w/ transaction costs	
		w/ banking	w/o banking	w/ banking	w/o banking
	p(t)	u(t)	u(t)	u(t)	u(t)
1	14.99	99	99	99	99
2	15.98	99	99	99	99
3	16.20	99	99	99	99
4	12.88	0	99	92	99
5	14.37	198	99	106	99
6	14.03	0	99	93	99
7	14.87	0	99	89	99
8	16.98	298	99	115	99
9	14.34	0	99	97	99
10	15.47	198	99	101	99
Total revenue ($)		15,638	14,861	12,569	12,534

Table 3.3 Farmer's NPV for expected revenues from agricultural production and credit sales, N runoff level, NM application decision and annually awarded credit at t=0

	Baseline[a]	w/o transaction cost	w/ transaction cost
NPV over a 10-year contract ($)	648,127	652,035	650,385
N runoff level (kg)	692	582	617
NM application level (ha)	-	47	28
annually awarded credit (kg)	-	110	75

[a] Baseline is the scenario that the farmer operates the farm at the optimal level and does not participate into the WQT program.

Table 3.4 Simulation results, including credit-selling path and nondiscounted total revenues from credit sales for endogenous NM application

Time period		Edog. NM application w/o transaction costs		Edog. NM application w/ transaction costs	
		w/ banking	w/o banking	w/ banking	w/o banking
	p(t)	u(t)	u(t)	u(t)	u(t)
1	14.99	99	99	67.5	67.5
2	15.98	99	99	67.5	67.5
3	16.20	99	99	67.5	67.5
4	12.88	0	99	61.2	67.5
5	14.37	198	99	73.5	67.5
6	14.03	0	99	63.5	67.5
7	14.87	0	99	57.5	67.5
8	16.98	298	99	81.5	67.5
9	14.34	0	99	66.9	67.5
10	15.47	198	99	68.1	67.5
Total revenues		15,638	14,861	9,001	8,971

Table 3.5 The impact of the drift of credit price on the gains from nutrient credit banking policy (holding other parameter value constant)

Time period	α=0			α=0.01 (Initial value)			α=0.02			α=0.03		
		w/ banking	w/o banking		w/ banking	w/o banking		w/ banking	w/o banking		w/ banking	w/o banking
	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)
1	13.56	67.5	67.5	14.99	67.5	67.5	16.56	67.5	67.5	18.31	67.5	67.5
2	14.46	67.5	67.5	15.98	67.5	67.5	17.66	67.5	67.5	19.52	67.5	67.5
3	14.66	67.5	67.5	16.20	67.5	67.5	17.90	67.5	67.5	19.79	67.5	67.5
4	11.65	67.5	67.5	12.88	61.2	67.5	14.23	60.6	67.5	15.73	59.8	67.5
5	13.01	67.5	67.5	14.37	73.8	67.5	15.89	74.4	67.5	17.56	75.2	67.5
6	12.70	67.5	67.5	14.03	63.5	67.5	15.51	63.1	67.5	17.14	62.6	67.5
7	13.45	67.5	67.5	14.87	57.5	67.5	16.43	56.5	67.5	18.16	55.3	67.5
8	15.36	67.5	67.5	16.98	81.5	67.5	18.77	83.0	67.5	20.74	84.6	67.5
9	12.97	67.5	67.5	14.34	66.9	67.5	15.84	66.9	67.5	17.51	66.8	67.5
10	14.00	67.5	67.5	15.47	68.1	67.5	17.09	68.1	67.5	18.89	68.2	67.5
Total revenues ($)		8,006	8,006		9,001	8,971		9,071	9,034		10,140	10,094
Gains from banking			0%			0.32%			0.41%			0.45%
Sensitivity index			0.32			-			0.09			0.065

Table 3.6 The impact of the volatility of credit price on the gains from nutrient credit banking policy (holding other parameter values)

Time period	σ = 0			σ = 0.01 (Initial value)			σ = 0.015			σ = 0.02		
		w/ banking	w/o banking		w/ banking	w/o banking		w/ banking	w/o banking		w/ banking	w/o banking
	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)	p(t)	u(t)	u(t)
1	15.472	67.5	67.5	14.99	67.5	67.5	14.75	63.0	67.5	14.50	56.8	67.5
2	15.472	67.5	67.5	15.98	67.5	67.5	16.23	72.0	67.5	16.49	78.2	67.5
3	15.472	67.5	67.5	16.20	67.5	67.5	16.57	67.5	67.5	16.94	67.5	67.5
4	15.472	67.5	67.5	12.88	61.2	67.5	11.75	52.9	67.5	10.71	35.9	67.5
5	15.472	67.5	67.5	14.37	73.8	67.5	13.85	82.1	67.5	13.34	79.0	67.5
6	15.472	67.5	67.5	14.03	63.5	67.5	13.36	48.0	67.5	12.71	39.0	67.5
7	15.472	67.5	67.5	14.87	57.5	67.5	14.57	51.5	67.5	14.27	51.7	67.5
8	15.472	67.5	67.5	16.98	81.5	67.5	17.78	103.0	67.5	18.62	132.1	67.5
9	15.472	67.5	67.5	14.34	66.9	67.5	13.79	60.0	67.5	13.27	53.4	67.5
10	15.472	67.5	67.5	15.47	68.1	67.5	15.46	75.0	67.5	15.44	81.6	67.5
Total revenues ($)		9,283	9,283		9,001	8,971		8,956	8,835		9,009	8,711
Gains from banking			0%			0.32%			1.36%			3.42%
Sensitivity index			0.32			-			2.08			3.1

Table 3.7 The impact of transaction costs associated with trading on the NM application level and the quantity of credit generated

	b=0.37, c=0.02 (Initial value)	b=0.37, c=0.05	b=0.37,c=0.08
NPV over a 10-year contract ($)	650,385	649,495	649,092
N runoff level (kg)	617	641	658
NM application level (ha)	28	18	11
annually awarded credit (kg)	75	51	34

Table 3.8 The impact of transaction costs and annually awarded credit quantity on the gains from banking

	b=0.37, c=0.02 (initial value)		b=0.37, c=0.05		b=0.37,c=0.08	
annually awarded credit (kg)	75		51		34	
	w/banking	w/o banking	w/banking	w/o banking	w/banking	w/o banking
p(t)	u(t)	u(t)	u(t)	u(t)	u(t)	u(t)
14.988	67.5	67.5	45.9	45.9	30.5	30.6
15.98	67.5	67.5	45.9	45.9	30.7	30.6
16.198	67.5	67.5	45.9	45.9	30.6	30.6
12.879	61.2	67.5	42.7	45.9	28.5	30.6
14.374	73.8	67.5	49.1	45.9	32.7	30.6
14.033	63.5	67.5	42.9	45.9	28.6	30.6
14.867	57.5	67.5	42.9	45.9	28.1	30.6
16.98	81.5	67.5	52.9	45.9	35.1	30.6
14.344	66.9	67.5	45	45.9	30.0	30.6
15.465	68.1	67.5	46.8	45.9	31.2	30.6
Total revenues	9001	8971	4459	4444	3759	3749
Gains from banking		0.3299%		0.3296%		0.2598%

Figures

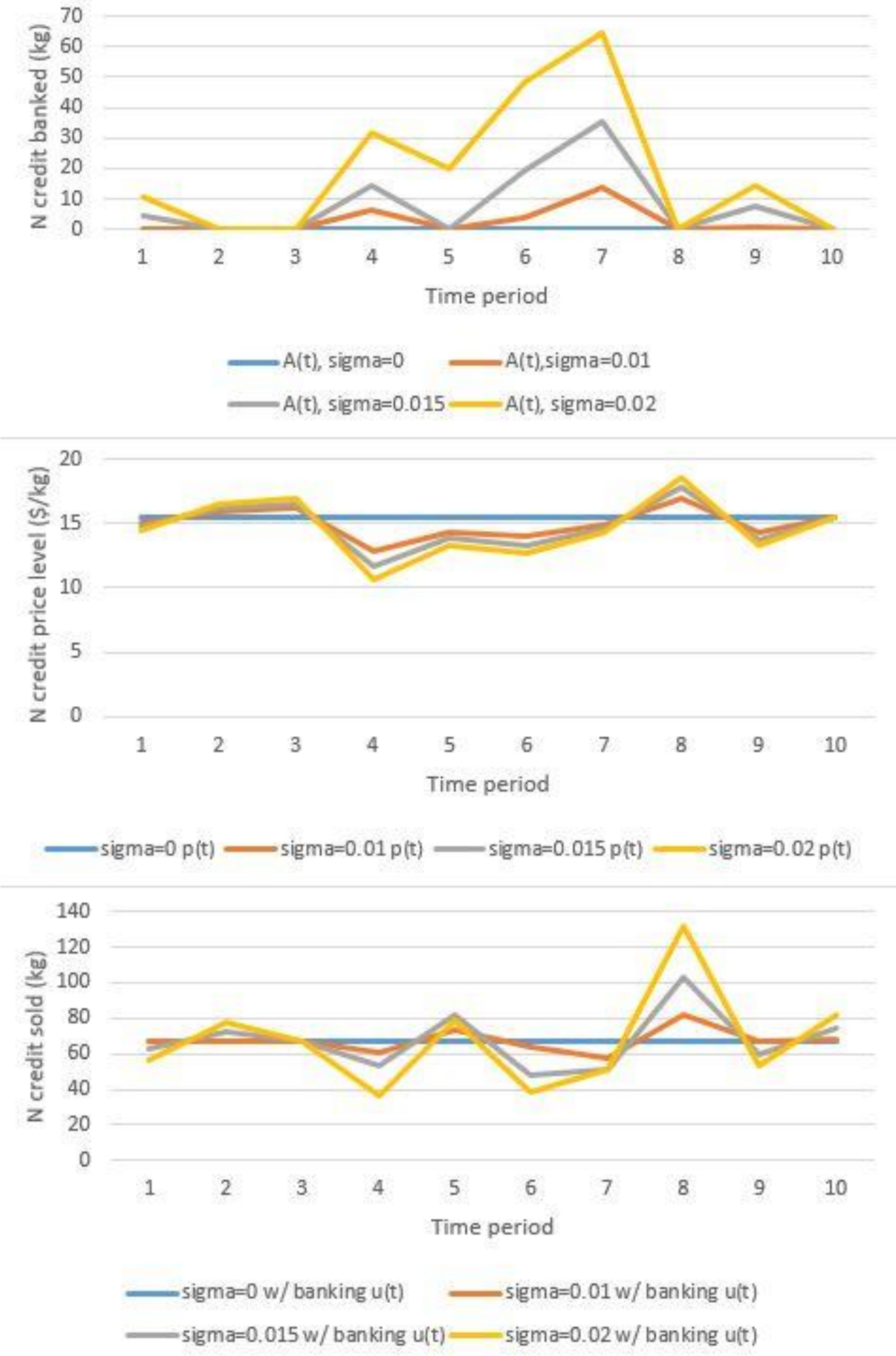

Figure 3.1 The impact of price volatility (middle panel) on the credit-banking path (top panel) and the credit-selling path (bottom panel)

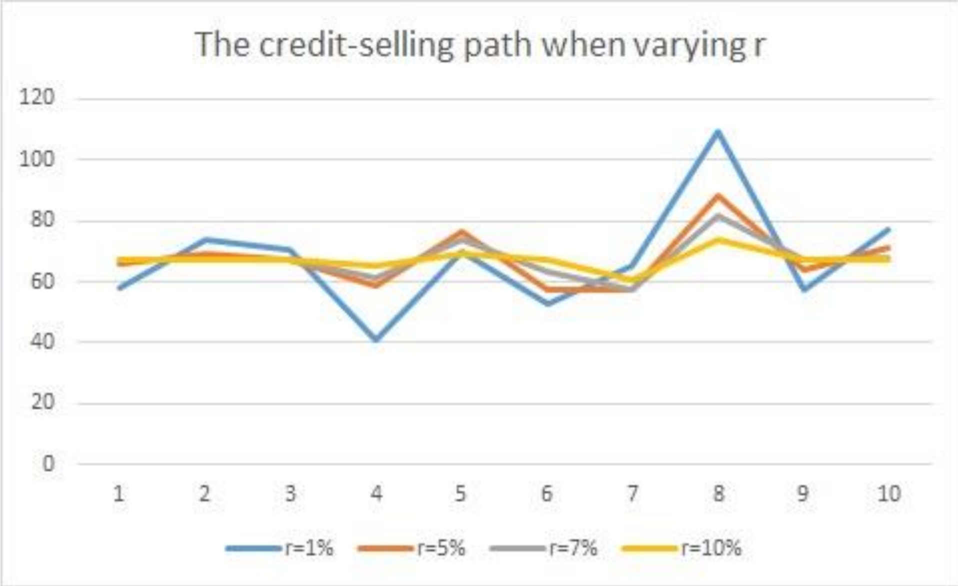

Figure 3.2 The impact of the interest rate on the credit-selling path

Appendix tables

Table App 3.1 Crop production budget[a]

	Price (2018$/Mg)	Cost (2018$/ha)[b]
Corn grain	249	967
Corn silage	60	1467
soybean	499	495
alfalfa	198	805

[a] Bosch et al., 2018

[b] Costs exclude land rent and fertilizer costs.

Table App 3.2 Livestock budget (2018 price level) [a]

	Gross revenue ($/unit)	Total costs ($/unit)	Net revenue ($/unit)
Dairy Cattle [b]	4,128	2,272	1,856
Beef Cow-calf [c]	844	407	437
Broiler [d]	0.3	0.07	0.23
Hog [b]	174	58	116
Layer [b]	42	24	18
Turkey [b]	29	27	2

[a] Gross revenue, total costs and net revenue are all adjusted to 2018 price level by multiplying their corresponding GDP deflators. See Bosch et al. (2018). Total costs exclude land rent and feed that can be raised or purchased and manure spreading.

[b] Penn State Extension, 2016

[c] Virginia Cooperative Extension, 2011

[d] University of Maryland Extension, 2011